World Development 127 (2020) 104744

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Tourism and local welfare: A multilevel analysis in Nepal's protected areas

Marie-Eve Yergeau

Global Affairs Canada, Canada

ARTICLE INFO

Article history:
Accepted 30 October 2019

JEL classification:
I31
Q26
O13

Keywords:
Welfare
Protected area
Tourism
Multilevel model

ABSTRACT

While environmental conservation is sometimes criticized for limiting the sources of income for the poorest populations, tourism in protected areas is often viewed in the literature as a mechanism that helps to increase local welfare and reduce poverty in developing countries. However, there are still few quantitative studies assessing how nature-based tourism is directly linked with welfare. In this article, we examine the relationships between: (1) tourism and the monetary welfare of local populations in Nepal's protected areas and (2) self-reporting being constrained in the use of natural resources, and the welfare of the same population. We develop a two-level hierarchical linear model to take into account the database structure. We estimate that households involved in a self-employed occupation directly linked to tourism are associated with a significantly higher consumption compared with non-involved households. In addition, results suggest that tourism may generate positive externalities on the community's welfare. We conclude that tourism development in Nepal's protected areas should be included in a broader sustainable development agenda.

1. Introduction

Environmental conservation and poverty alleviation are two major issues in developing countries. However, the nature of the relationship between these two concerns is still a matter of debates in the scientific literature (Brockington & Wilkie, 2015). Some authors associate poverty with a non-sustainable use of natural resources caused by, among other things, population growth, fertile land inaccessibility, and insufficient resources allocated to a sustainable management of the natural environment (e.g. Mink, 1993; Reardon & Vosti, 1995; Forsyth, Leach, & and Scoones, 1998; Scherr, 2000). Others criticize conservation policies in developing countries for their role in limiting both the expansion of agriculture and resource use, especially since natural resources are one of the main sources of income for the poorest populations (Brockington & Wilkie, 2015). Nevertheless, the establishment of protected areas has become a widespread practice designed to curb environmental degradation. Indeed, between 1990 and 2014, the world's protected area has increased from 13.4 millions km^2 to 32 million km^2 and now covers nearly 15% of the land surface (UNEP, 2014). In developing countries, protected areas are often established in remote areas where poverty rates are higher (Dudley, Mansourian, Stolton, & and Suksuwan, 2008). However, mechanisms can be implemented in order to mitigate the negative impacts induced by the protected areas on the poorest. Some of these mechanisms include offering a direct monetary compensation for environmental initiatives, while others opt for integrating conservation efforts into a global development strategy (Coad, Campbell, Miles, & and Humphries, 2008). Nature-based tourism is also one of these mechanisms, and it is becoming increasingly embedded in national poverty reduction strategies (Yunis, 2004; Goodwin, 2006; Chok, Macbeth, & Warren, 2007).

In this article, we study the relationships between tourism, environmental constraints, and local monetary welfare in Nepal's protected areas. Our analysis has two main purposes. First, we examine the link between tourism and household welfare in highly visited protected areas. In order to do so, we estimate the relationship between being involved in an occupation directly linked to tourism and household consumption. In addition, we examine if being involved in tourism is linked with an increase or a decrease of other households consumption in the same community. To our knowledge, this is the first analysis of this relationship based on a unit of analysis as disaggregated as the household, that also assesses potential externalities of tourism on welfare.

Second, we examine the relationship between self-reported resource use restrictions and household welfare. All households

E-mail address: marie-eve.yergeau@usherbrooke.ca

https://doi.org/10.1016/j.worlddev.2019.104744
0305-750X/

included in the sample are required to respect environmental rules due to the fact that they live inside a protected area. Among these households, we distinguish the ones that self-report being constrained in their resource use because of the restrictions from the ones that self-report being not constrained. Then, we measure the relationship between self-reporting being constrained, and consumption. This matter is important as a significant relationship would indicate that compensation mechanisms should be implemented and targeted towards households that self-report being constrained in their use of natural resources.

To answer these questions, we develop a two-level hierarchical linear model that we estimate using original Nepalese data. In the literature, the scarcity of studies on relationships between protected areas, welfare, and mechanisms that moderate this relationship such as tourism is often explained by the lack of appropriate data (Coad et al., 2008; Ferraro & Hanauer, 2014). In this analysis, we use data that have been collected for the specific purpose of studying these relationships. Using a multilevel approach is appropriate considering the database hierarchical and clustered structure. Indeed, multilevel modeling allows combining and analyzing relationships modeled on different hierarchical levels. Estimates show that, under certain conditions, tourism in protected areas is significantly and positively linked to welfare, while self-reporting being constrained in natural resource use is not.

2. Background

2.1. Protected areas, tourism, and welfare

Few quantitative studies isolate and measure the effect of environmental conservation on welfare and poverty reduction, particularly in developing countries. Furthermore, results are mixed. On the one hand, theoretical models are generally based on the hypothesis that environmental policies constrain the optimal use of land and thus generate a local welfare decrease (e.g. Robalino, 2007; Anthon, Lund, & Helles, 2008; Robinson, Albers, & Williams, 2008; Robinson & Lokina, 2011). On the other hand, empirical studies show that the establishment of protected areas has contributed to economic development and/or to poverty reduction (e.g. Andam, Ferraro, Sims, Healy, & Holland, 2010; Bandyopadhyay & Tembo, 2010; Sims, 2010;Ferraro & Hanauer, 2011; Ferraro, Hanauer, & Sims, 2011; Naughton-Treves, Alex-Garcia, & Chapman, 2011; Canavire-Bacarreza & Hanauer, 2013; Robalino & Villalobos-Fiatt, 2015; Yergeau, Boccanfuso, & Goyette, 2017; den Braber, Evans, & Oldekop, 2018). These analyses are often conducted using matching methods[1] that implicitly make the assumption that all households associated with a given measure of protection, or subgroups of households when considering heterogeneous effects, are equally affected by conservation policies. Therefore, they do not allow verifying whether conservation causes welfare gaps between households that are required to respect the same environmental rules. Moreover, these studies do not formally measure mechanisms through which conservation contributes to improving welfare. Indeed, while some mechanisms are suggested, such as migration (Sims, 2010), infrastructure development (Ferraro & Hanauer, 2011; Canavire-Bacarreza & Hanauer, 2013), and tourism (Sims, 2010; Ferraro & Hanauer, 2011; Ferraro et al., 2011; Richardson, Fernandez, Tschirley, & Tembo, 2012; Canavire-Bacarreza & Hanauer, 2013; Robalino & Villalobos-Fiatt, 2015; den Braber et al., 2018), very few authors have measured their relationship with welfare. Among the few, Ferraro and Hanauer (2014) have developed a statistical framework to study the impact of different mechanisms, in Costa Rica's protected areas. They attribute nearly half of the effect of conservation on welfare to tourism development. In addition, Yergeau, Boccanfuso and Goyette (2017) show theoretically and empirically that the effect of protected areas on local welfare is moderated by tourism development.

While studies on mechanisms linking conservation and welfare are rare, costs and benefits for populations living inside protected areas are documented and discussed in the literature (Coad et al., 2008; Brockington & Wilkie, 2015). A review of these costs and benefits is proposed in Coad et al. (2008). Expropriation and population displacements, property rights transfer to the government, restrained access to forest resources, and human-wildlife conflicts are included in the cost of conservation. The prevention of soil erosion and natural disaster, water access, forest resource availability, infrastructure development, and the protection of cultural and religious traditions constitute some of the benefits of conservation. Further, other benefits, such as Payments for Ecosystem Services (PES), Integrated Conservation and Development Programs (ICDPs), and tourism including ecotourism and nature-based tourism, have the potential to generate an alternative income for local populations. However, none of these means is considered as being an optimal solution for reaching the goals of environmental conservation and poverty reduction simultaneously (e.g. Adhikari, 2005; Grieg-Gran, Porras, & Wunder, 2005; Baral, Stern, & Heinen, 2007; Nagendra & Gokhale, 2008). Nevertheless, studies have shown that in developing countries, tourism is positively linked to economic growth (Weinberg, Bellows, & Ekster, 2002; Eugenio, Morales, & Scarpa, 2004; Sequeira & Nunes, 2008; Hunt, Durham, Driscoll, & Honey, 2014; Mbaiwa, 2015), employment (Weinberg et al., 2002; Neto, 2003; Yunis, 2004; Hunt et al., 2014; Mbaiwa, 2015) and that it is a major source of exports (Neto, 2003; Yunis, 2004).

Tourism in protected areas is considered by several authors as having the potential of generating a local income and improving the welfare of populations (e.g. Adams et al., 2004; Richardson et al., 2012; WTO, 2013; Ferraro & Hanauer, 2014; Yergeau, 2015). According to Metcalfe (2003), it is an efficient mechanism for combining a sustainable use of natural resources with development projects (Metcalfe, 2003[2]). Further, tourism development is increasingly embedded in poverty reduction strategies (Yunis, 2004; Goodwin, 2006; Chok et al., 2007). Yet, robust quantitative studies based on objective indicators measuring the relationship between tourism and local welfare are scarce (Meng, Li and Uysal, 2010).

2.2. The case of Nepal

Nepal has experienced recent progress in growth and human development, yet, it remains one of the least developed countries in the world. In 2014, 25.2% of the population was living under the national poverty line (ADB, 2016). Moreover, Nepal ranks 144th out of 188 countries on the Human Development Index (UNDP, 2016). The agricultural sector, that contributes for 35% of the GDP, employs 75% of the labor force. However, most farmers are poor (Basnett et al., 2014). Indeed, nearly 80% of households in rural areas are involved in subsistence farming (IFAD, 2014). In addition, due to geographical disparities, crops productivity is unequal between the different regions of the country. Indeed, Nepal is divided into three ecological zones: the Terai in the south, the hills in the center, and the mountains in the north. Altitude thus varies from 70 meters above sea level in the Terai, up to 8,848 meters in the mountains (mount Everest). Terai is suitable for agriculture, whereas in the mountains, farming conditions are difficult, and soil is poor. These geographical disparities are reflected in the living conditions. For instance, in 2011, poverty rates in the hills and Terai were less than 25% (24.32% and 23.44% respectively), while it was of 42.27% in the mountains

[1] Except for Sims (2010) and Yergeau et al. (2017) who both use regression methods on household data.

[2] Cited in Coad et al. (2008).

(CBS, 2011). Remoteness, difficulty of access as well as poor communication networks and infrastructures also explain the high poverty rate in the mountains area (IFAD, 2013).

Nepal is also characterized by a rich yet fragile natural environment. The country faces environmental challenges such as deforestation, land degradation, biodiversity loss, melting glaciers, and pollution (RRN & CECI, 2007). In response to these challenges, a system of protected areas has been progressively established. Designation of protected areas began in 1973 with the passing of the National Parks and Wildlife Conservation Act. A very strict regulation authorizing the Government to withdraw resources use rights and to expropriate local populations was implemented to control deforestation and poaching (Shrestha et al., 2010). Later, Fig. 1 due to several conflicts between the government and residents, amendments to the law were proposed so that protected areas' designation now combines conservation goals with the development of sustainable economic opportunities (Keiter, 1995; Heinen & Shrestha, 2006). Today there are 20 protected areas including 12 national parks, 1 wildlife reserves, 6 conservation areas, 1 hunting reserve. There is also a total of 13 buffer zones (DNPWC, 2018) (Fig. 1). The main goal of national parks and wildlife reserves is to protect biodiversity and ecosystems, while conservation areas, hunting reserve, and buffer zones aim at promoting a sustainable use of resources, by combining economic and social development to environmental conservation initiatives (IUCN, 2016). Furthermore, about 75% of Nepal's protected areas aims to involve local populations in resource management, and in the sharing of conservation benefits (Budhathoki, 2005).

Since the opening of the borders to foreigners in the 50s, the country's natural resources and its cultural heritage have attracted many visitors (Nepal, 2000). Nowadays, the Government of Nepal considers tourism as a major sector of the economy (DNPWC, 2014). In 2014, 790,000 tourists entered on the Nepalese territory (WTTC, 2015). Among them, nearly 55% visited a protected area. Tourism in Nepal's protected areas mostly offers locally run nature-oriented and cultural experiences.[3] It is noteworthy that our analysis cannot be generalized to including mass tourism.[4] The total contribution[5] of the tourism sector was evaluated to 8.9% of the GDP and it represented 7.5% of total employment (WTTC, 2015). Tourism in protected areas is perceived among residents as improving non-farm employment opportunities and providing incentives for resource conservation (Mehta and Kellert, 1998). Studies have also shown that local populations have a positive attitude towards tourism (Mehta and Kellert, 1998; Spiteri & Nepal, 2008a). Finally, Nepal (2000) concluded that tourism allowed remote regions such as the Everest and the Annapurna, to lift out of poverty.

3. Method

3.1. Study sites

Data were collected in three different protected areas: the Annapurna Conservation Area, the Langtang National Park, and the Chitwan National Park Buffer Zone.[6] These areas have been selected according to three criteria: accessibility by ground transportation,[7] the time elapsed since the protected area has been designated and the importance of tourism inside the area, as measured by the number of international tourist arrivals in 2012 (c.f. Table 1. The complete list of protected areas in Nepal along with their designation year and number of tourist arrivals in 2012 is presented in appendix A). These criteria allowed selecting areas characterized by a sufficiently important length of protection and tourism activity so that residents could evaluate their impact.

3.1.1. The Annapurna Conservation Area

The Annapurna Conservation Area (ACA) is the largest protected area in Nepal (7,629 km^2). It is managed by the National Trust for Nature Conservation (NTNC), a local NGO. Its objectives are to "(1) conserve the natural resources for the benefit of present and future generations, (2) bring sustainable social and economic development to the local people and (3) develop tourism in such a way that it will have minimum negative impact on the natural, socio-cultural and economic environments" (NTNC, 2019). The Annapurna Conservation Area Project (ACAP) was initiated in 1986 as a small scale pilot project because of environmental degradation from population and tourism pressures. Due to its success, it was then expanded significantly in 1989, and again in 1993 (Spiteri & Nepal, 2008b). It was officially notified as a "Conservation Area" in 1992 (NTNC, 2019).

ACAP was the first protected area that allowed local residents to maintain their traditional rights and access to the use of natural resources (NTNC, 2019). The conservation area's management plan utilizes a zoning scheme to protect the most fragile areas while authorizing resource use activities in the other areas. For instance, it includes wilderness areas centered on most fragile areas, protected forests and seasonal grazing zones to meet basic subsistence needs, and intensive multiple-use zones to accommodate villagers and tourists (Keiter, 1995). Because they depend on natural resources, most of residents are concerned with the future availability of resources, which has proven being beneficial to conservation (Spiteri & Nepal, 2008b).

NTNC receives no regular funding support from the government for the operation of ACAP, but it has been granted the right to collect entry fees from visiting trekkers. This revenue is then invested back into the region, its resources and its community (NTNC, 2019). Today, because of its attractive features and easy accessibility, ACAP is the most popular trekking destination in the country. Tourism, that is concentrated in villages and regions along the main trekking routes, is one of the main sectors of the economy (NTNC, 2019). It provides employment and economic opportunities, although most of is only seasonal (Spiteri & Nepal, 2008b).

3.1.2. Langtang National Park

The Langtang National Park has an area of 1,710 km^2 and an altitude ranging between 1,000 and over 7,000 meters. It is managed by the Department of National Parks and Wildlife Conservation, an entity of the Ministry of Forest and Environment. Its objectives include, among others, to protect ecosystems and biodiversity, to promote the culture of indigenous people and provide sustainable livelihoods opportunities, to promote ecotourism, and to promote research and monitoring programs (Government of Nepal, 2014).

While the establishment of the park in 1976 was associated with a restricted use of natural resources, local people were still granted the right to use park resources for purposes such as grazing livestock within designated areas, and collecting grass, fodder, fuel wood and construction timber at low cost. Nevertheless, regulations were very strict and enforced by the army. Then starting in the 80s, local people were recognized as integral to protected areas management and essential elements of conservation. Over the years, rules were thus modified to include people needs. For instance, in 1996, a buffer zone of 420 sq. km. was established to

[3] According to our on-site observations and welcomenepal.com.

[4] We refer to mass tourism as an extreme concentration of tourists in one place compared to the local population density (Theng, Qiong, & Tatar, 2015).

[5] As defined in WTTC, 2015, p. 2.

[6] The municipality of Bharatpur was excluded from the sample design. It is an urban area that is not suitable for nature-based tourism.

[7] For instance, because of budget and time constraints, the Sagarmatha National Park (Everest region) that has been designated in 1976, and attracts a relatively high number of tourists (c.f. Appendix A) could not be considered as it is only accessible by plane (high cost) or by foot (several days trek).

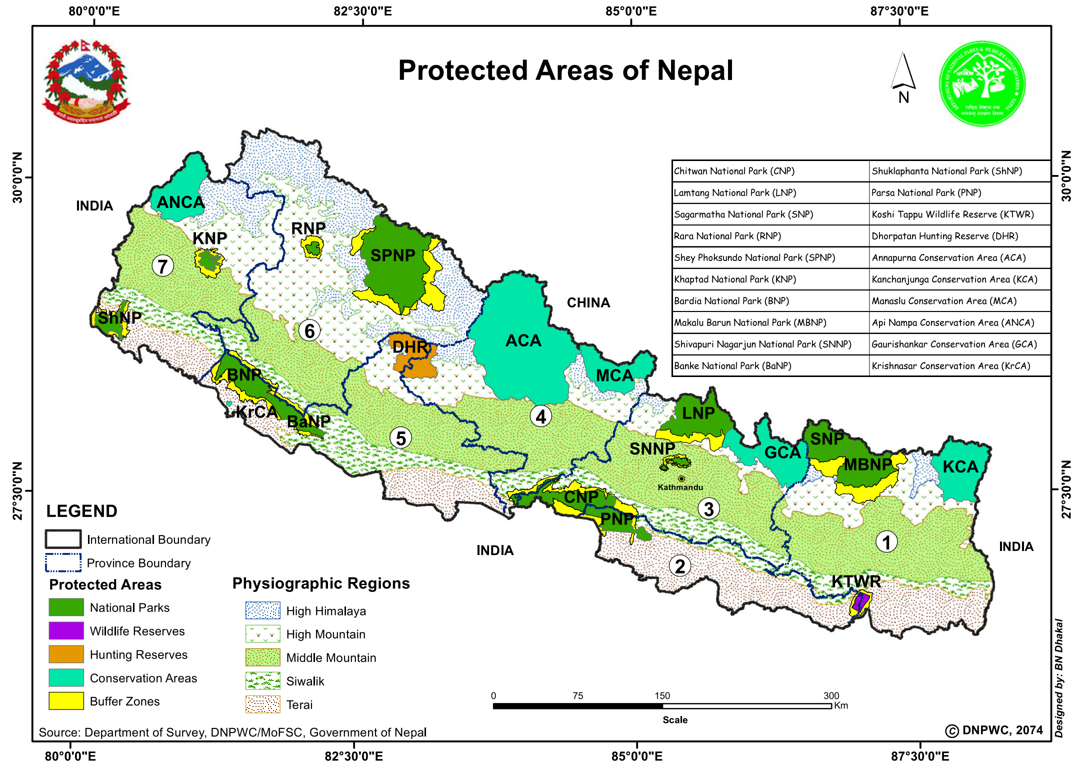

Fig. 1. Protected areas in Nepal. Source: DNPWC (2018).

Table 1
Description of selected protected areas.

	Designation year[a]	Area (km^2)[b]	Number of tourists in 2012[c]	Population in 2011[d]	Number of VDCs[e,f]	Number of selected VDCs	Number of interviewed households
Annapurna C.A.	1992	7,629	102,570	59,570	57	4	536
Langtang N.P.	1976	1,710	14,315	17,619	26	3	491
Chitwan B.Z.	1996	750	170,112[h]	93,334[g]	18	3	536

[a] DNPWC (2014).
[b] protectedplanet.net.
[c] MTCA (2013).
[d] CBS (2012).
[e] The VDC is defined in the next section.
[f] Information provided on site by the Central Bureau of Statistics.
[g] Excluding the municipality of Bharatpur.
[h] Number of tourists that accessed the Chitwan National Park. The information on the number of tourists in the buffer zone is not available.

give a better access to resources to communities living inside and around the park (Bhattarai et al., 2017).

In addition, in 2007, the Langtang National Park and its buffer zone were included in a new project, called "Langtang National Park and Buffer Zone Support Project", initiated by WWF Nepal. The primary goal of the project is to "conserve biodiversity, enhance livelihoods opportunities and sustain diverse cultures and traditions by integrated management of land, forest and water resources in Langtang National Park and Buffer Zone". Moreover wildlife conservation activities, the project supports improving livelihoods of communities through tourism and community-based management of natural resources (WWF, 2019). Being the nearest Himalayan Park from Kathmandu, the Langtang National Park is today the third most popular trekking destination among all protected areas of Nepal.

3.1.3. Chitwan National Park Buffer Zone

The Chitwan National Park covers 932 km^2 of the Terai region, with an altitude ranging from 110 to 850 meters. Established in 1976, it is the oldest protected area in Nepal. Following the Park designation, traditional use of resources has been banned and prior permission had to be received from the park authority to enter the park legally. Consequently, local people were significantly disadvantaged by the restricted access to their traditional livelihoods (Bhattarai et al., 2017). Therefore, to foster balance between the long-term conservation objectives and immediate needs of local residents, a buffer zone of 750 km^2 surrounding the park was established in 1996 (Dhakal & Thapa, 2015).

A buffer zone is an area surrounding a park or a reserve encompassing forests, agricultural lands, settlements, village open spaces and any other land use. The buffer zone programme in Nepal is a major strategy to preserve protected areas through community-based natural resource management in their periphery. This main goal of the Chitwan National Park Buffer Zone is thus "gaining people's participation in managing park resources for biodiversity conservation and improving livelihood opportunities of the buffer zone communities". Since its designation, it has been managed on participatory approach by Chitwan National Park and buffer zone management communities (Government of Nepal, 2015).

More than half (55%) of the buffer zone is usable wildlife habitat including forests, grasslands, and rivers; the rest is agriculture land and settlements. A majority of people rely on subsistence agriculture but dependence on agriculture is decreasing as the younger generation turns to off-farm activities including tourism (Lamichhane et al., 2017). Most of tourism in the buffer zone is located near of the Chitwan National Park few entries. Chitwan is one of the most popular tourist destinations in Nepal. It is particularly known for its safaris.

3.2. Data and methodological justification

The data were collected between August and December 2013.[8] The sample includes 1,563 households selected according to a random multistage sample design.[9]

Administrative divisions were used to elaborate a random multistage sample design, that was repeated in the three protected areas. Using administrative divisions was appropriate as it allowed to concentrate the survey in a few locations, which reduced time and costs. Because they were selected at random, sample weights could be calculated to assure a representative sample of the selected protected areas. First, Village Development Committees (VDC) were selected with probability proportional to the VDC's size of the population.[10] Second, with all selected VDCs divided into nine wards, the number of households per ward that had to be interviewed was determined with probability proportional to the size of the ward's population.[11] Finally, households in each ward were selected by systematic sampling.[12] Table 6 in Appendix C summarizes the database structure.

Given the sample design, observations are clustered on different hierarchical levels. Indeed, as shown in Fig. 2, households (level 1) belong to a ward (level 2), and wards belong to a VDC (level 3). Therefore, all households that belong to a same ward and VDC are likely to share similar characteristics and thus to violate the assumption of independence of observations. Consequently, standard estimation methods based on this assumption are not appropriate (Deaton, 1997; Cameron & Miller, 2010; Hox, 2010).

In the empirical literature, different methods are suggested to estimate relationships with clustered data. For instance, including in the model a cluster-specific fixed effect to capture the between-cluster heterogeneity is a common approach. However, this method does not allow including in the model variables that are invariant between observations that belong to a same cluster, such as the ward share of households involved in tourism, which is constraining when these variables are of interest. Another option is to include these variables of interest in the model instead of a fixed effect. However, for the assumption of independence of observations to be satisfied, they would have capture all the between-cluster heterogeneity, which may be a challenging condition (Steenbergen & Jones, 2002).[13] The multilevel model allows to relax this condition by including a random error term on each analysis level, that captures the between-cluster heterogeneity that is not explained by the regressors. For instance, it will capture the effect of ward-level geographical features that are correlated with both the dependent variable and the variables of interest, that cannot be included in the model due to lack of data. It thus allows modeling relationships between variables measured on different levels, the dependent variable being measured at the inferior level, while capturing dependence between observations of a same level (Hox, 1998, 2010).

3.3. Multilevel model

The multilevel model is a generalization of the traditional regression model in which one or more random effects, other than the one associated with the individual error term, are included. The general form of the multilevel model is presented in Appendix D.

In this article, we define a two-level hierarchical linear model. Levels are defined by the database structure: The household represents the level-1 unit, and the ward represents the level-2 unit. Level-1 variables are thus measured at the household level, and level-2 variables are measured at the ward level, i.e., level-2 variables do not vary between households in a same ward. It is noteworthy that the VDC is not included in the model as a third level. Indeed, simulations have shown that including a level composed of a small number of units produces biased estimations.[14] Therefore, the sample containing only 10 different VDCs, the VDC cannot be included as a third level. Instead, a fixed effect capturing the heterogeneity between the VDCs is added.[15]

The two-level hierarchical linear model may be represented by a hierarchical structure of regression models. In that structure, one or more coefficients associated with the independent variables measured at the inferior level, and the intercept, are random parameters defined at the superior level. These parameters thus vary between second-level units. Let i represents the first level unit (i.e. the household) and j, the second level unit (i.e. the ward). The first level of the model is:

$$y_{ij} = \beta_{0j} + \sum_{p=1}^{P} \beta_{pj} x_{pij} + \epsilon_{ij} \tag{1}$$

where y_{ij} is the dependent variable for household i in ward j, x_{pij} are the P level-1 independent variables and ϵ_{ij} is the individual random error.

We observe in (1) that parameters β_0 and βp are random (i.e. they are indexed j and thus vary between wards). The second level of the model is composed of the set of equations that characterizes these random parameters. Intuitively, second-level equations define how the intercept and the effect of explanatory variables on the dependent variable vary between wards.

Let z_{qj}, the Q level-2 independent variables. The intercept is thus defined by:

$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} z_{qj} + u_{0j} \tag{2}$$

---

[8] It is noteworthy that the survey was approved by an institutional ethics committee for research on human subjects.

[9] The weighted sample counts 170,157 households, which is consistent with the 2011 census population of 170,523 households (author calculations from CBS (2012)).

[10] A VDC is an administrative division similar to the municipality.

[11] The ward is the smallest administrative division. A few wards had to be excluded from the sample design because of accessibility issues. For more information see Yergeau (2017).

[12] For more information on the sample design, see Appendix B.

[13] For more details on estimation with clustered data, see for instance Wooldridge (2003) or Cameron and Miller (2010).

[14] For instance, Maas and Hox (2005) obtain standard deviation estimates 15% too small with a sample composed of 30 level-2 units, while Jia, Stokes, Harris, and Wang (2011) note that at least 20 per-level units are required to produce reliable estimates. Snijders and Bosker (2012) also recommend a minimum of 20 units.

[15] We also ran the model including a protected area's fixed effect. As it was non-significant and did not change results, it was excluded from the final model.

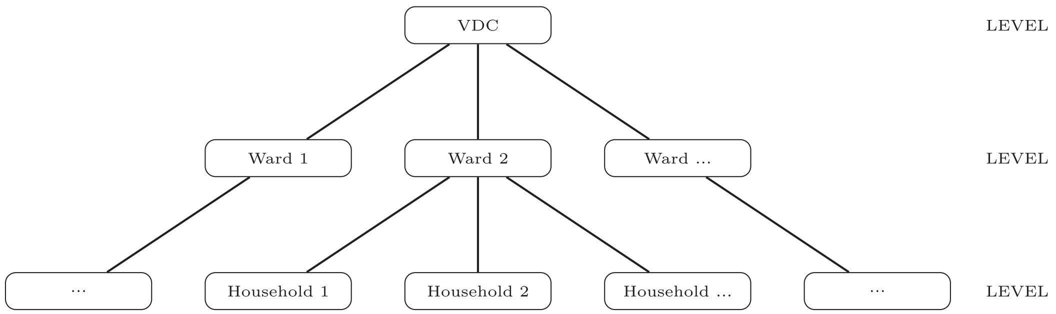

Fig. 2. Database structure.

where γ_{00} is the mean intercept, common to all observations, and u_{0j} is the random term. Therefore, wards' intercept deviation from the mean γ_{00}, is explained by the z_{qj} explanatory variables, and the rest of the deviation is assumed to be random and captured by u_{0j}.

Regression coefficients are defined by:

$$\beta_{pj} = \gamma_{p0} + \sum_{q=1}^{Q} \gamma_{pq} z_{qj} + u_{pj}, \quad p = 1, \ldots, P \tag{3}$$

where γ_{p0} is the mean effect of variable p on the dependent variable, common to all observations, and u_{pj} is the random term. Therefore, wards' regression coefficient deviation from the mean γ_{p0}, is explained by the z_{qj} explanatory variables, and the rest of the deviation is assumed to be random and captured by u_{pj}.

It is noteworthy that β_{pj} may be assumed to be fixed. Then, $\beta_{pj} = \beta_p$, for all j, and the effect of explanatory variable p on the dependent variable does not vary between wards. In addition, coefficients γ_{0q} and γ_{pq} may be constrained to equal zero so that first-level random parameters do not have to be explained by the same set of level-2 variables. Combining (1)–(3) lead to the final model:

$$y_{ij} = \left[\gamma_{00} + \sum_{p=1}^{P} \gamma_{p0} x_{pij} + \sum_{q=1}^{Q} \gamma_{0q} z_{qj} + \sum_{p=1}^{P}\sum_{q=1}^{Q} \gamma_{pq} z_{qj} x_{pij}\right] + \left[\sum_{p=1}^{P} u_{pj} x_{pij} + u_{0j}\right] + \epsilon_{ij} \tag{4}$$

Random effects follow a multivariate normal law such as:

$$\begin{pmatrix} u_{0j} \\ \vdots \\ u_{pj} \end{pmatrix} \sim \mathcal{N}\left[\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} \begin{pmatrix} \sigma_{00}^2 & \cdots & \sigma_{0p} \\ \vdots & \ddots & \vdots \\ \sigma_{p0} & \cdots & \sigma_{pp}^2 \end{pmatrix}\right] \tag{5}$$

Therefore, u_{0j} and u_{pj} have a constant variance and may be correlated, and between-level error terms are orthogonal.

3.4. Estimation strategy and simulations

We estimate the model using a pseudo-maximum likelihood approach. This method is recommended when including sample weights in the model is needed (Asparouhov, 2006; Rabe-Hesketh & Skrondal, 2006; Jia et al., 2011). Because using sample weights in a multilevel model is likely to generate an overestimation of the variance of random effects.[16] (e.g. Pfeffermann et al., 1998; Jia, Stokes, Harris, & Wang, 2011; Rabe-Hesketh & Skrondal, 2006), we also estimate the model using a scaling method. To determine which scaling method should be used, we run simulations that reproduce our sample design and database structure. For more information on the estimation approach, the scaling, and the simulations, see Appendix E.

4. Variables

Table 2 contains mean values for all variables, for the complete sample, that it the sample including all households (column "Complete"), for the group of households involved in tourism[17] (column "Involved"), and for the group of households not involved in tourism (column "Not involved"). The last column contains minimum and maximum values for the complete sample.

4.1. Dependent variable

Monetary welfare is measured by households annual consumption expenditures.[18] In the literature, it is generally recognized that expenditures are smoother and less affected by short term fluctuations than income (Deaton & Zaidi, 2002). In addition, expenditures are considered as a better monetary welfare measure as they are more directly linked to basic needs satisfaction and less prone to measurement errors (World Bank, 2016).

To build the variable, we use the method recommended in Deaton and Zaidi (2002). Consumption expenditure is calculated by aggregating expenses for goods and services on a 12 months period. It aggregates expenses on 30 food items (self-produced, bought on the market, and received in-kind), 41 non-food items, 16 durable goods, 10 facilities and amenities, education, and housing. More details can be found in Yergeau (2017). Expenditures are expressed per adult equivalent in order to take into account heterogeneity in households composition and intra-household reallocation. We use the Oxford equivalence scale, which gives a weight of one consumption unit to the first adult, 0.7 unit to other household members aged of 14 and older, and 0.5 unit to children under 14.

The average annual household consumption expenditure per adult equivalent is 160, 257 Nepalese rupees (NPR). It is noteworthy that there is a welfare gap (significant at 1%) between households that are involved in tourism and households that are not involved in the sector. Indeed, average consumption for the first group is 264, 782 NPR, which is nearly twice the average consumption of the second group.

[16] Let us recall that random effects are the random terms associated with superior level equations, as modeled in (2) and (3) They are not directly estimated but characterized by their variance.

[17] The household "involved in tourism" is defined in Section 4.2.1.

[18] It is noteworthy that consumption expenditures are expenses that cover the household's consumption only. It does not include, for instance, business expenses.

Table 2
Description of variables for the complete sample and by status of involvement in tourism.

Variable description	Mean			Min–max
	Complete	Involved	Not involved	Complete
Dependent variable				
Consumption expenditures (in NPR)***	160,257	264,782	138,979	11,259–8,440,485
Variables of interest				
Environmental restrictions 1 (env1)	0.24	0.32	0.22	0–1
Environmental restrictions 2 (env2)	0.19	0.31	0.16	0–1
Involvement in tourism – wage job[a]	0.07	0.40	0.00	0–1
Involvement in tourism – self-employed[a]	0.12	0.68	0.00	0–1
Share of ward involved – wage job***	0.07	0.18	0.05	0–0.5
Share of ward involved – self-employed***	0.12	0.29	0.08	0–1
Control variables				
Sex of household head (=1 if masculine)**	0.78	0.84	0.77	0–1
Age of household head	47.03	45.48	47.34	16–96
Household size*	4.01	4.27	3.96	1–17
Share of HH aged − of 15 and + of 60 ***	0.34	0.27	0.35	0–1
Superior caste (=1 if yes)***	0.33	0.24	0.35	0–1
Dalit (=1 if yes)***	0.06	0.03	0.07	0–1
Maximum level of education in household***	10.54	11.67	10.31	0–21
Share of household unemployed***	0.30	0.21	0.32	0–1
Share of household in farming sector***	0.45	0.32	0.47	0–1
Share of household self-employed[b]	0.12	0.10	0.12	0–1
Received remittances (=1 if yes)***	0.26	0.17	0.28	0–1
Size of owned land (in Ropani)***	8.36	5.51	8.94	0–160.74
Log. of residence value (in NPR)***	13.65	14.20	13.55	9.90–18.42
Distance from market[c]	2.80	2.73	2.81	1–5
Number of institutions at less than 2 km[d]	2.28	2.25	2.29	0–3
Bus stop at less than 0.5 km (=1 if yes)	0.41	0.42	0.41	0–1
Collected wood in the forest (=1 if yes)	0.56	0.52	0.56	0–1
Observations	1,563	275	1,288	1,563

***1% significance of the difference between "involved" and "not involved" subsample means. ** 5% significance. *10% significance.
[a] Variable not standardized, = 1 if household is involved, = 0 otherwise.
[b] In a sector other than farm and tourism.
[c] =1:more than 10 km, =2:between 5 and 10 km, =3: between 2 and 5 km, =4: between 0.5 and 2 km, =5: less than 0.5 km.
[d] Among primary school, secondary school, and health center.

4.2. Variables of interest

Six variables of interest are created to measure the effect of tourism and environmental restrictions on local welfare.

4.2.1. Tourism

In order to distinguish households that are involved in tourism from households that are not involved, we use the survey question: "Did you or any member of your household derive any economic benefit from tourists during the past 12 months?" (answer yes or no). Households who answered *yes* are considered as being involved in the tourism sector and represent 18% of the sample. Among involved households, we create two categories: (1) households involved in tourism in a wage job and (2) households self-employed in tourism. Most of wage jobs in the sample consist of working as a guide or as a porter in the mountains, or doing different tasks in a hotel or a restaurant, while most of self-employed own a hotel or a restaurant. A household thus belongs to the first category if at least one household member is involved in tourism in a wage job and to the second category if at least one household member is self-employed in tourism. Let us mention that a household can belong to both categories. We distinguish these two job categories as they are likely to be characterized by a welfare gap. Indeed, the average annual consumption of households in the first category is $131,288$ NPR, while it is $346,279$ NPR in the second.

Two indicators are thus created:

1. ind^{wage}: Takes the value of 1 if the household is involved in tourism in a wage job and 0 otherwise;
2. ind^{self}: Takes the value of 1 if the household is self-employed in tourism and 0 otherwise.

Next, we transform these indicators to build variables in order to estimate intra-group and inter-group coefficients. When observations in a same cluster are correlated, level-1 explanatory variables are likely to affect the dependent variable through two potentially distinct and independent effects: (1) an individual or intra-group effect and (2) a cluster or inter-group effect. Intra-group regression coefficients thus measure average individual effects of explanatory variables on the dependent variable for observations in a same cluster. As for inter-group coefficients, they capture intra-cluster average effects of explanatory variables, on the intra-cluster mean of the dependent variable (Snijders & Bosker, 2012). Details on intra-group and inter-group coefficient calculation are presented in Appendix G.

Therefore, we first calculate the mean of indicators ind^{wage} and ind^{self} for each ward (intra-cluster mean). These variables, respectively named $tourward^{wage}$ and $tourward^{self}$, will allow estimating inter-group coefficients. Intuitively, they measure the ward's share of households involved in tourism, in a wage job or as self-employed. They will allow to estimate the effect of the ward's share of households involved in tourism on the ward's average welfare.

Second, to estimate intra-group coefficients, we center indicators ind^{wage} and ind^{self} with respect to their intra-cluster mean. These variables, named $tour^{wage}$ and $tour^{self}$, will thus allow to estimate the effect of getting involved in tourism, in a wage job or as self-employed, on individual welfare.

Variables included in the regression model are thus defined as:

- $tourward^{wage}$: Share of households in the ward involved in tourism in a wage job (intra-cluster mean of ind^{wage})
- $tour^{wage}$: Indicator ind^{wage} centered with respect to the intra-cluster mean ($ind^{wage} - tourward^{wage}$).
- $tourward^{self}$: Share of households in the ward involved in tourism as self-employed (intra-cluster mean of ind^{self})
- $tour^{self}$: Indicator ind^{self} centered with respect to the intra-cluster mean ($ind^{self} - tourward^{self}$)

4.2.2. Environmental restrictions

In order to measure the relationship between self-reporting being constrained in the use of natural resources, and welfare, we create two variables out of survey questions. Households included in the sample all lived in a protected area and were thus required to respect certain rules regarding the use of natural resources.[19] It is noteworthy that in all sites visited, resource collection was limited at different levels, but not forbidden. Households defined as "constrained" are those who claim that if these rules did not exist, they would use more natural resources while households defined as "non-constrained" would not use more natural resources. Therefore, to distinguish "constrained" and "non-constrained" households, we use the two following survey questions.

1. If your village was not protected, your household would collect more resources in the forest. Do you: agree/not agree/do not know?
2. If your village was not protected, your household crop production would be more important. Do you: agree/not agree/do not know?

We create two dummy variables, one for each question. Households associated with the value of 0 are considered non-constrained with regard to the related question. Households associated with the value of 1 are considered constrained.

Variables included in the model are thus defined as:[20]

- $env1$: Indicates if the household is constrained in its use of forest resources.
- $env2$: Indicates if the household is constrained in its crop production.

4.2.3. Test of structural stability

Since economic opportunities generated by the establishment of protected areas are likely to encourage households to migrate towards these areas, a potential selection bias cannot be excluded. For instance, if a household decides to move in a protected area with the prospect of getting involved in the tourism sector, it self-selects itself in the group of households involved in the tourism sector. Involved households are thus likely to share common characteristics, such as skills for running a tourism business or owing relatively more capital, that could in turn bias the relationship between being involved in tourism, and welfare. To rule out this source of bias, we run a Chow test to verify the structural stability between households that were living on the area's territory before it was protected (49.5% of the sample) and the ones that have migrated in the area after its designation ($50,5\%$ of the sample). All coefficients associated with variables of interest are statistically equal for the two sub-samples, except for the ones associated with the variable $tour^{wage}$, which is however strongly non-significant. We thus conclude that household migration towards protected areas is not a source of bias.

4.3. Control variables

Control variables are included in the model to capture the effect of factors that are correlated with both consumption and the variables of interest, that might make households more likely to get involved in tourism, or to self-report being constrained in their use of natural resources. They were selected based on a review of the literature on relationships between protected areas, tourism and welfare (Ferraro & Hanauer, 2011; Sims, 2010; Ferraro et al., 2011; Richardson et al., 2012; Canavire-Bacarreza & Hanauer, 2013), and on poverty in Nepal (Bhatta & Sharma, 2006; Baland, Bardhan, Das, Mookherjee, & Sarkar, 2010; Lokshin, Bontch-Osmolovski, & Glinskaya, 2010), as well as on data availability.

To control for household characteristics, we include the sex and age of the household head, the household size, and the share of household members aged of less than 15 and more than 60 years old. Moreover, two variables indicate whether the household belongs to a high caste (Brahmin, Chhetri or Newar) or whether the household belongs to the inferior caste of Dalit.[21] We measure human capital by the maximum level of education in the household. To take into account employment and other sources of income, we include the share of household members: (1) aged of 15 or more and unemployed, (2) working in the farm sector, and (3) self-employed in a sector other than farming and tourism. We also include a variable indicating whether the household received remittances during the 12 months preceding the survey. To take into account physical capital owned by the household, we include the size of owned land and the value of the residence. Access to infrastructures is included through variables measuring the distance from a market, from a bus stop,[22] from a primary and a secondary school, and from a health center. Finally, a variable indicates whether or not the household collected firewood in the forest during the 12 months preceding the survey.

5. Models and results

5.1. Fixed effects model

First of all, we estimate a traditional OLS model including ward fixed effects. Because ward fixed effects are included, the model omits ward-level variables. Results are presented in Table 3, columns (1) and (2). They are consistent with results obtained using the multilevel model, which shows that multilevel results are not driven by the choice of statistical approach. Consequently, for the sake of brevity, multilevel results only will be discussed.

5.2. Random intercept empty model

The first step when using a multilevel model is to investigate for between-cluster heterogeneity (i.e. correlation between intra-cluster observations), to confirm the relevance of this type of model compared with a one-level model, such as the OLS model estimated previously. To do so, we estimate an empty model in

[19] Rules intensity is taken into account by control variables.

[20] Inter-group and intra-group regression coefficients associated with theses variables are not estimated. Indeed, several model specifications including the intra-cluster mean of $env1$ and $env2$ were tested. In all cases, variables were non-significant.

[21] See Bennett, Dahal, and Govindasamy (2008) for more information on caste classification.

[22] Most of the villages included in the sample did not have a formal bus stop. Individuals had to go along the main route and signal the bus driver to stop. This variable thus also captures the distance from a main route.

Table 3
Results.

	Consumption expenditures											
	OLS				Multilevel 1				Multilevel 2			
Scaling	–		–		No		Yes		No		Yes	
Intercept	11.95***	(0.067)	11.28***	(0.197)	11.39***	(0.136)	11.388***	(0.142)	12.189***	(0.662)	13.166***	(1.041)
Tourism involvement – wage	0.119	(0.118)	0.155	(0.098)	0.056	(0.084)	0.077	(0.079)	0.122	(0.080)	0.103	(0.071)
Tourism inv. – self-emp.	0.762***	(0.103)	0.508***	(0.083)	0.666***	(0.126)	0.736***	(0.119)	0.500***	(0.105)	0.524***	(0.100)
Environmental restriction 1	0.068	(0.074)	0.090	(0.060)	−0.052	(0.044)	−0.027	(0.039)	0.017	(0.036)	−0.025	(0.044)
Environmental restriction 2	−0.162	(0.103)	−0.111*	(0.065)	0.007	(0.033)	−0.066	(0.036)	0.016	(0.045)	−0.079	(0.054)
Tourism ward – wage					−0.556	(0.407)	−0.661*	(0.399)	−0.232	(0.588)	−0.137	(0.540)
Tourism ward – self-emp.					1.175***	(0.329)	1.306***	(0.366)	1.027***	(0.380)	1.055***	(0.410)
Sex of HH head			−0.025	(0.066)					0.005	(0.040)	−0.043	(0.035)
Age of HH head			0.003*	(0.002)					−0.000	(0.002)	0.002*	(0.001)
HH size			−0.07***	(0.020)					−0.077***	(0.019)	−0.075***	(0.014)
High caste			0.052	(0.050)					0.159**	(0.067)	0.039	(0.077)
Dalit			−0.111	(0.088)					−0.183***	(0.035)	−0.182***	(0.036)
Education max. in HH			0.033***	(0.005)					0.035***	(0.004)	0.032***	(0.004)
Share of HH aged <15 and >60			−0.160	(0.100)					−0.130**	(0.060)	−0.150***	(0.041)
Share of HH unemployed			−0.036	(0.091)					0.035	(0.053)	0.013	(0.074)
Share of HH in farm sector			−0.154**	(0.080)					−0.133**	(0.058)	−0.064	(0.075)
Share of HH self-empl.			0.590***	(0.112)					0.400***	(0.086)	0.533***	(0.096)
Size of owned land			0.004*	(0.002)					0.008***	(0.002)	0.004***	(0.001)
Distance from market			0.067***	(0.014)					0.045*	(0.026)	0.064**	(0.030)
Received remittances			0.100**	(0.054)					0.100***	(0.035)	0.137***	(0.027)
No. of institutions at 2 km or -			0.009	(0.024)					0.044*	(0.025)	0.001	(0.016)
Value of residence (log)			0.016***	(0.006)					0.019***	(0.003)	0.019***	(0.005)
Collected wood in forest			−0.34***	(0.054)					−0.155***	(0.042)	−0.283***	(0.061)
Bus stop at less than 0.5 km			0.260***	(0.050)					0.100***	(0.032)	0.195***	(0.060)
Ward fixed effects	Yes		Yes		No		No		No		No	
Other fixed effects[a]	No		Yes		No		No		Yes		Yes	
Random effects												
σ^2_u					0.100	(0.025)	0.073	(0.028)	0.055	(0.010)	0.024	(0.012)
$\sigma^2_{tour^{wi}}$					0.090	(0.036)	0.000	(0.000)	0.102	(0.037)	0.000	(0.000)
$\sigma^2_{tour^{si}}$					0.200	(0.056)	0.073	(0.036)	0.192	(0.062)	0.076	(0.039)
σ^2_ϵ					0.360	(0.017)	0.392	(0.022)	0.260	(0.020)	0.279	(0.020)
Observations	1,563		1,563		1,563		1,563		1,563		1,563	

***1% significant. **5% significant. *10% significant. Robust standard errors in parenthesis.
[a] Include VDC, protected areas and month fixed effects.
Covariances between random effects constrained to 0. Consumption expenditures are in logarithm and expressed per adult equivalent. $\sigma^2_{tour^{wi}}$ is the variance of the coefficient associated with the variable of involvement in a tourism wage job. $\sigma^2_{tour^{si}}$ is the variance of the coefficient associated with the variable of involvement in tourism as self-employed.

which only a random intercept is included. The model and results are presented in appendix F. Results confirm the existence of between-ward heterogeneity. Therefore, using a multilevel model is appropriate for this analysis.

5.3. Random coefficients model

To measure relationships between tourism, self-reported environmental constraints, and household welfare, we estimate the model:

$$y_{ij} = \beta_{0j} + \beta_{1j} tour^{wage}_{ij} + \beta_{2j} tour^{self}_{ij} + \beta_3 env1_{ij} + \beta_4 env2_{ij} + \sum \beta_p X_{pij} + \epsilon_{ij} \quad (6)$$

$$\begin{aligned} \beta_{0j} &= \gamma_{00} + \gamma_{01} tourward^{wage}_j + \gamma_{02} tourward^{self}_j + u_{0j} \\ \beta_{1j} &= \gamma_{10} + u_{1j} \\ \beta_{2j} &= \gamma_{20} + u_{2j} \end{aligned} \quad (7)$$

where y_{ij} is the welfare of household i in ward j, ϵ_{ij} is an individual error term and u_0j, u_1j u_2j are random effects. In this model, (6) is the level-1 model specification and (7) is the level-2. We observe in (6) that the intercept β_{0j} and coefficients β_{1j} and β_{2j} are random parameters. The intercept β_{0j} is interpreted as the average level of welfare in ward j, given regressors in (6). As shown in the first equation of (7), the intercept is explained by the ward's share of households involved in tourism, in a wage job ($tourward^{wage}_j$) and as self-employed ($tourward^{self}_j$). The variation of the between-ward intercept that is not explained by these two variables is assumed to be random and captured by u_{0j}.

Second and third equations in (7) show that coefficients β_{1j} and β_{2j} vary randomly between wards according to a random term. Therefore, it is assumed that the effect of getting involved in a wage job (as self-employed) in the sector of tourism, on household welfare, deviates randomly between wards from the average effect in the population, γ_{10} (γ_{20}), according to the variance of u_{1j} (u_{2j}).

Coefficients associated with environmental restriction variables, β_3 and β_4, are fixed. Their variance is close to 0, indicating that the effect of the variables does not seem to vary between wards. Finally, X_{pij} is a control variable vector. All coefficients associated with these variables are fixed. Results without control variables (Model 1) and with control variables (Model 2), with and without scaling, are presented in Table 3.

In appendix E, we have tested and validated statistical equality between regression coefficients with and without scaling. Therefore, if (6) and (7) are well specified, estimations with and without scaling should also be statistically equal. We use a Wald test to verify statistical equality between scaled and unscaled estimates. The statistic follows a Student law with 1,562 degrees of freedom, and the covariance between coefficients is obtained by simulation over 500 iterations. The Wald test confirms statistical equality between scaled and unscaled coefficients for the variables of interest, which is consistent with simulation results.

As expected, relationships between tourism and household welfare differ according to the job category. Indeed, neither getting involved in a tourism wage job ($tour^{wage}$), nor the ward's share of household involved in a tourism wage job ($tourward^{wage}$) is significantly related to welfare. However, being self-employed in tourism ($tour^{self}$) is positively and significantly related to welfare. In fact, households self-employed in tourism are associated with a consumption expenditure that is on average nearly 65% higher compared with non-involved households.[23]

The coefficient associated with the variable $tourward^{self}$ is also positive and significant. Therefore, there is a positive relationship between the ward's share of households involved in a self-employed occupation in tourism, and the ward's average welfare. In addition, results suggest that self-employment in tourism is associated with intra-ward positive externalities. Indeed, as shown in appendix G, the inter-group coefficient associated with the variable $tourward^{self}$ (γ_{02}) represents the sum of two terms: the intra-group coefficient, that is the one associated with the variable $tour^{self}$ (β_{2j}), and an additional term that is calculated by $(\gamma_{02} - \beta_{2j})$. Intuitively, the first term (β_{2j}) captures the ward's average welfare increase caused by the welfare increase of households getting self-employed in tourism. The second term $(\gamma_{02} - \beta_{2j})$, captures the externalities that increase the welfare of all households in the ward, independently of their individual involvement in the sector. Since $(\gamma_{02} - \beta_{2j})$ is positive, externalities are positive.

The variance of the coefficient associated with being self-employed in tourism is statistically different from 0, with and without scaling, meaning that the relationship between self-employment in tourism and household welfare vary between wards. This suggests that characteristics that are common to households belonging to a same ward, or characteristics of the ward itself, affect the relationship between tourism and welfare. Identifying these characteristics in a future study would be relevant to specify conditions allowing to optimize the effect of tourism on welfare. To do so, the use of variables related to geographic characteristics, disaggregated at the ward level, would be necessary. To our knowledge, such data are not currently available.[24]

Finally, relationships between self-reporting being constrained in the use of natural resources and welfare are non-significant. Relationships between control variables and welfare are discussed in appendix H.

5.4. Random coefficients model by protected areas

In order to compare relationships between variables across protected areas, we run model (6)–(7) for each protected areas, that is for the Annapurna Conservation Area, the Langtang National Park and the Chitwan National Park Buffer Zone. All specifications include scaled sampling weights. Results are presented in Table 4.

Being involved in a tourism wage job is significantly and positively related to welfare in the Annapurna and Langtang areas, while the relationship is negative in the Chitwan Buffer Zone. On average, households involved in a tourism wage job have a consumption 24% higher than non-involved households in the Annapurna area, 5% higher in the Langtang Area and 10% lower in the Chitwan area. Being self-employed in tourism is significantly and positively related to welfare in the Annapurna and Chitwan areas, while the variable is non-significant in the Langtang area. Relationship magnitudes for the Annapurna and Chitwan areas are similar to the one calculated for the whole sample (c.f. Table 3).

Coefficients associated with the variable $tourward^{self}$ are positive and significant for all protected areas. A higher ward's share of households self-employed in tourism is thus associated with a higher ward's consumption, in all protected areas. However, the magnitude differ between areas: the relationship is a lot stronger in the Annapurna compared with Langtang and Chitwan. Furthermore, results suggest that in the Chitwan Buffer Zone, an increase in the ward's share of households self-employed in tourism would be associated with a welfare decrease for households in the ward that are not involved in the same job category. Indeed, since $(\gamma_{02} - \beta_{2j})$ is negative, externalities are negative.

Finally, random effects are relatively small, indicating that most of the inter-ward variation estimated when using the whole sample occurs between wards of different protected areas. However, this results must be interpreted cautiously. Indeed, the number of wards reduces significantly when running regressions for each protected area. As discussed in Section 3.3, this might affect the robustness of random effects estimates.

6. Cook's distance test

To ensure results are not biased by one or more influential wards, we conduct a Cook's distance test as suggested in Snijders and Berkhof (2008).[25] In multilevel analysis, the Cook's distance measures the influence of a second-level unit on the value of all parameters (Möhring & Schmidt, 2012). Details are presented in Appendix I The test confirms that results are robust with regard to the cluster effect as they that are not generated by influential wards.

7. Discussion and conclusion

In this study, we develop a two-level hierarchical linear model to estimate relationships between environmental restrictions, tourism development, and local welfare in Nepal's protected areas. Our results corroborate the hypothesis suggested in the literature: tourism development in protected areas can be positively linked to an increase of local welfare (Sims, 2010; Ferraro & Hanauer, 2011; Ferraro et al., 2011; Richardson et al., 2012; Canavire-Bacarreza & Hanauer, 2013; Robalino & Villalobos-Fiatt, 2015; den Braber et al., 2018). We distinguish households according to their job category because there is a significant difference in the consumption between the two categories. In our sample, the average annual consumption of wage earning households is 131,288 NPR, while for self-employed households it is 346,279. The relationship between each job category and welfare are thus likely to differ. When considering the whole sample, our estimates show that becoming involved in tourism in a wage job is not significantly linked to a welfare variation, while becoming self-employed in the sector is positively related with consumption. When breaking down the sample into protected areas, our results show positive relationships between being involved in a tourism wage job and welfare in the Annapurna Conservation Area and the Langtang National Park, and a negative relationship in the Chitwan National Park Buffer Zone. Nevertheless, in all cases, coefficients for the wage job involvement variable remain smaller than for the self-employment variable, indicating that the relationship between self-employment in tourism and welfare is relatively stronger.

Occupations included in each job category are characterized by very different working conditions, which is certainly a factor

[23] $\triangle\%y = 100(\exp(\beta) - 1)$.

[24] In an extension of the article, appropriate data could be generated using GIS. These data include, but are not limited to distance to a main city, to a park entrance, to a summit, and to a watershed. Other variables such as average temperature, rainfall and snowfall, maximum elevation, and soil quality would also be of interest. While generating these data is out of scope of this article, it should be included in a future study.

[25] For more details on the test, see Snijders and Bosker (2012, p. 167–172).

Table 4
Results by protected areas.

	Consumption expenditures					
	Annapurna C.A.		Langtang N.P.		Chitwan N.P.B.Z.	
Intercept	14.860***	(0.410)	7.739***	(0.420)	12.142***	(0.159)
Tourism involvement – wage	0.217***	(0.078)	0.046***	(0.017)	−0.109**	(0.043)
Tourism inv. – self-emp.	0.534***	(0.114)	0.287	(0.307)	0.504***	(0.058)
Environmental restriction 1	0.002	(0.034)	0.125	(0.141)	0.057	(0.071)
Environmental restriction 2	−0.059	(0.062)	−0.045	(0.115)	−0.061	(0.069)
Tourism ward – wage	−0.644	(0.613)	−0.239	(0.526)	−0.108	(0.197)
Tourism ward – self-emp.	1.058***	(0.349)	0.240**	(0.114)	0.200*	(0.114)
Control variables	Yes		Yes		Yes	
Fixed effects[a]	Yes		Yes		Yes	
Random effects						
σ_u^2	0.000	(0.000)	0.005	(0.008)	0.000	(0.000)
$\sigma_{tour^{wi}}^2$	0.000	(0.000)	0.000	(0.000)	0.020	(0.036)
$\sigma_{tour^{si}}^2$	0.047	(0.000)	0.321	(0.374)	0.012	(0.025)
σ_ϵ^2	0.276	(0.000)	0.236	(0.050)	0.277	(0.051)
Observations	536		491		536	

***1% significant. **5% significant. *10% significant. Robust standard errors in parenthesis.
[a] Include VDC and month fixed effects.
Covariances between random effects constrained to 0. Consumption expenditures are in logarithm and expressed per adult equivalent. $\sigma_{tour^{wi}}^2$ is the variance of the coefficient associated with the variable of involvement in a tourism wage job. $\sigma_{tour^{si}}^2$ is the variance of the coefficient associated with the variable of involvement in tourism as self-employed.

explaining differences in results between the two categories. In total, 83% of wage jobs in tourism occupied by the respondents consisted of working as a guide or as a porter in the mountains, or doing different tasks in a hotel or a restaurant. Other jobs were related to transportation and ticketing. Several of these workers reported being remunerated irregularly, on a daily-basis. Further, working conditions are mostly unregulated. Therefore, improving working conditions for wage-workers, for instance by increasing wages or by creating more regular jobs, should be part of a poverty reduction strategy. Groups, associations and NGOs could also contribute to improving working conditions. For instance, the International Porter Protection Group (IPPG) was created in Nepal in 1997 with the aim of providing access to adequate clothing, shelter and food, medical care, and insurance to porters (IPPG, 2019). Another example is the Tourist Guide Association of Nepal (TURGAN), founded in 1989, whose goal is to safeguard and protect Nepal's tourist guides' interests. For instance, according to a local paper, they have been negotiating with the Nepal Association of Tour and Travel Association in 2018 for an increase in wages for tourist guides.[26] TURGAN also provides advice and expertise to the government concerning tourism promotion and advancement (TURGAN, 2010). Finding ways to expand the reach of such organizations could help improve and maintain working conditions for wage workers. Finally, offering skills development training in guiding, cooking, handicrafts and English language, among others, would contribute to increasing the quality of services workers may offer. More qualified workers could expect higher salaries and higher welfare.

While being involved in a tourism wage job is not significantly linked to welfare when considering the whole sample, the relationships become significant when the sample is broken down by protected areas. We observe a positive relationship between being involved in a tourism wage job in the Annapurna and Langtang areas, while the relationship is negative in the Chitwan Buffer Zone. From an economic perspective, one explanation could be that the Annapurna and Langtang regions are remote and besides tourism and agriculture, there are few other economic opportunities. The Chitwan area is easily accessible, more developed, with more opportunities. In the Annapurna and Langtang areas combined, the mean income of households involved in a tourism wage job is, in adult equivalent, 150,000 NPR compared with 144,000 NPR in the Chitwan Buffer Zone. However, the total mean income in the Annapurna and Langtang combined is 146,000 NPR, compared with 196,000 NPR in the Chitwan Buffer Zone. Therefore, in the Chitwan Buffer Zone, there seem to be other, more lucrative economic activities available for skilled workers that make a tourism wage job less attractive compared with the two other regions. This could be a factor explaining why a tourism wage job is not welfare enhancing in Chitwan while it is in the two other areas.

Households self-employed in tourism reported owning a business related to lodging, fooding, garments selling, transportation or guiding services. These enterprises often generated intra-household work and were more lucrative compared with wage jobs. Developing local businesses in the tourism sector should thus be encouraged as long as there is a demand for these services and that the market is not saturated. Certainly, there are more barriers to entry to opening a tourism business than to working in a wage job, which is probably a factor explaining the difference in results between the two categories. Actions should thus be taken to address these barriers. For instance, facilitating access to credit, particularly in remote areas where financial services are scarce (UNDP, 2015), would increase households' investment capacity. Again, proposing short and appropriate training programs related to entrepreneurship, small business management, and hospitality would allow increasing skills required to develop, improve, and diversify tourism services. Infrastructure development, including roads, electricity, and telecommunications, would facilitate and secure traveling. Finally, consolidating the tourism offering around a local development strategy in order to foster complementarity between services would potentially contribute to increasing the positive externalities produced by the sector.

Our estimations also indicate that the relationship between becoming self-employed in tourism and welfare varies across wards. Characteristics that are common to households belonging to a same ward, or characteristics of the ward itself, thus moderate the relationship between tourism and consumption. Further investigation is needed to identify these characteristics; however, it suggests that geographical features, among other factors, are likely to interfere in the relationship between tourism and welfare. This is in line with Yergeau, Boccanfuso and Goyette (2017) who show theoretically that when conservation allows a productive sector

[26] http://www.newbusinessage.com/Articles/view/9058.

such as tourism to develop, the relationship between conservation policies and welfare varies according to geographical features. Our result also supports several applications on the relationship between protected areas and welfare, in which authors suggest that conservation will contribute to welfare as long as benefits generated by an alternative sector exceed the opportunity cost of conservation (Sims, 2010; Ferraro & Hanauer, 2011; Ferraro et al., 2011; Richardson et al., 2012; Canavire-Bacarreza & Hanauer, 2013). Finally, it reinforces our argument that the relationship between being involved in a wage job and welfare varies across protected areas because of differences in the availability of economic opportunities, that may depend on geographical and communities' features.

We also estimated the relationship between the ward's share of households involved in tourism and the ward's average welfare. Our results show that tourism may generate positive externalities. This is important as it suggests that at least part of the income derived from tourism is spent or redistributed locally. Tourism in developing countries is often criticized on the grounds that it only benefits a small group of the population and that revenues are taken out of local communities (e.g. Goodwin & Roe, 2001; Simpson, 2007). Our results show that in Nepal's protected areas, the income that is kept locally is sufficient to be associated with a welfare increase in the community, even for households that are not involved in the sector. This reinforces our argument that developing small and local tourism businesses in Nepal's protected areas should be part of a local development strategy. However, in the Chitwan Buffer Zone, the results show that tourism is associated with negative externalities. Given that tourism activity in Chitwan is very concentrated around a few park entrances, this result could indicate the presence of strong competition in the tourism industry and market saturation. Indeed new actors joining the sector would affect others negatively by capturing market share.

Turning to protected areas' restrictions on resources, our estimations indicate that self-reporting being constrained in the use of natural resources is not significantly associated with household welfare. This result supports studies such as Andam et al. (2010), Sims (2010), Ferraro and Hanauer (2011), Ferraro et al., 2011; Canavire-Bacarreza and Hanauer (2013); Robalino and Villalobos-Fiatt (2015) who find that protected areas do not generate a welfare decrease. However, because our variables are built out of hypothetical questions, our results must be interpreted cautiously for the following reasons.

Our results could suggest that local populations in protected areas have adapted to environmental restrictions. Protected areas included in the sample were designated between 1973 and 1992. Households living inside these areas, being either constrained or not, are thus likely to have developed mechanisms to maintain a certain consumption level in spite of any restrictions.

However, the non-significance of coefficients could also indicate that households do not respect rules. Indeed, even though rules exist, it does not mean they are entirely enforced or respected. On the one hand, if households use more resources than they are allowed to, they may not feel constrained while they would if they respected the rules. On the other hand, if households use more resources than they are allowed to in order to maintain a certain consumption level, but report being constrained anyway, being constrained is likely not to be related with their welfare.

Another factor to consider is that while households may feel constrained because of the rules, the rules might be the reason why they can still use resources. Indeed, studies have indicated that protected areas in Nepal contributed to more sustainable resource management (e.g. Spiteri & Nepal, 2008b; Bhattarai et al., 2017). Therefore, without the restrictions, resources could have disappeared. From that perspective, rules may have a positive effect on welfare that would not be captured in the hypothetical questions used in this study.

The last reason to consider is that the average consumption expenditures of non-constrained households is 170,728 NPR, which is significantly higher than the average consumption of constrained households of 138,094 NPR.[27] Let us recall that constrained households consider themselves constrained in their use of forest resources and/or in their crop production. Therefore, while our results do not show a significant, direct relationship between resource use constraints and welfare, it seems that constrained households are characterized by a lower welfare level compared to non-constrained households. In addition, the fact that poorer people rely relatively more on natural resources has been widely discussed in the literature (e.g. Scherr, 2000; OECD, 2009; Brockington & Wilkie, 2015). We thus recall the importance of combining natural resource use restrictions with compensation mechanisms for local populations. To draw clear conclusions, our results should be subjected to further investigation through a more complex modeling process and the use of objective indicators.

Finally, results obtained by breaking down the sample into protected areas can be linked to theoretical models on tourism development and welfare such as Butler (1980), England and Albrecht (1984) and Yergeau, Boccanfuso and Goyette (2017). As in these models, our estimations suggest that there may be a correlation between the intensity of tourism development and welfare. Let us recall that between the three protected areas considered in the study, the number of tourist arrivals is lowest in the Langtang area and highest in the Chitwan area. Results obtained for the Annapurna and Langtang areas are in line with Yergeau, Boccanfuso and Goyette (2017). Indeed, these authors show that the strength of the positive relationship between tourism and welfare increases with the number of tourist arrivals. In this study, we find that the positive relationship between tourism and welfare is stronger in the Annapurna than in Langtang, where the number of tourists arrival is lower. As for results obtained in the Chitwan area, they are in line with Butler (1980), who show that from a certain level of tourist arrivals, an increase of tourism generates a welfare decrease. In a future study, the existence of such a threshold, where the relationship between tourism and welfare becomes negative, should be investigated further.

It is noteworthy that protected areas where the study was conducted attract a lot of tourists, which may have influenced the results, and limits the potential of generalization. In addition, our analysis did not take into account environmental impacts of tourism, such as pollution, accumulation of garbage, deforestation, and soil erosion, that may in turn affect welfare (Nepal, 2000). A model including these external effects should be part of a future analysis.

Our results are relevant for a country such as Nepal, considering the importance of the protected areas system and the tourism sector. In addition, the Government of Nepal considers tourism as one of the most promising sectors for the development of the country (Acharya and Halpenny, 2013). Our findings support the relevance of developing sustainable tourism in Nepal, as well as the United Nations recommendation to promote tourism in order to attain objectives of development and environmental conservation. To go further, a monetary and non-monetary welfare analysis and a distributive effect study should be conducted. Additionally, examining the effect of other mechanisms through which protected areas may contribute to welfare would be useful to understand better the relationship between environmental conservation and welfare. Finally, should robust and appropriate data become available, a longitudinal analysis would allow for a stronger causality measurement.

[27] 10% significance.

8. Acknowledgements

I would like to thank IDRC and the GRÉDI for their financial support. I also thank Dorothée Boccanfuso (Université de Sherbrooke) for her help and support, Stéphane Mussard (Université de Nîmes) for his helpful comments, and three anonymous referees for their comments and suggestions.

Appendix A. Protected areas in Nepal

Table 5

Appendix B. Sample design

Administrative divisions were used to elaborate a random multistage sample design, which was repeated in the three protected areas.

B.1. First stage: Selection of VDCs

First, VDCs belonging to each protected areas were identified using information provided by the Nepal's Central Bureau of Statistics, to elaborate three sampling frame (one for each protected area). Second, VDCs were selected from the sampling frames with probability proportional to size sampling. The measure of size that was used is the VDC's total households number, as identified in the 2011 census. Therefore, a VDC's probability of selection was increasing with the size of its population. A VDC's probability of selection, π_j, is calculated by:

$$\pi_j = a\frac{N_j}{\sum_{j=1}^{J} N_j} \quad (8)$$

where a is the number of VDCs selected in the protected area, N_j is the number of households in the VDC j and J is the total number of VDCs in the protected area.

In total, four VDCs were selected in the Annapurna Conservation Area, three in the Langtang National Park and three in the Chitwan National Park Buffer Zone. The Annapurna total area (7,629 km^2) is significantly higher than the area of Langtang (1,710 km^2) and Chitwan (932 km^2), which explains why a supplementary VDC was selected.

Table 5
Protected areas in Nepal.

Protected area	Year of designation	Number of tourists in 2012[a]
Chitwan National Park	1973	170,112
Sagarmatha National Park	1976	35,671
Langtang National Park	1976	14,315
Rara National Park	1976	124
Shey-Phoksundo National Park	1984	536
Khaptad National Park	1984	12
Bardiya National Park	1988	10,962
Makalu Barun National Park	1991	1,342
Shivapuri Nagarjun National Park	2002	154,845
Banke National Park	2010	0
Shukla Phanta National Park	1976	517
Parsa National Park	1984	343
Koshi Tappu Wildlife Reserve	1976	5,704
Annapurna Conservation Area	1992	102,570
Kanchanjangha Conservation Area	1997	309
Manaslu Conservation Area	1998	3,162
Krishnasaar Conservation Area	2009	0
Api Nampa Conservation Area	2010	0
Gaurishankar Conservation Area	2010	N/A
Dhorpatan Hunting Reserve	1987	77

[a] MTCA (2013).

B.2. Second stage: Selection of households

To select households in each selected VDCs, a two-step procedure was elaborated and followed.[28]

First, the number of households that would have to be interviewed in each ward of the VDC was calculated. Let us recall that a ward is an administrative division, smaller than the VDC, and that each VDC was divided into nine wards, of different sizes and compositions. Similarities in living conditions were often observed between households belonging to a same ward, while important disparities could be observed between households belonging to different wards, in a same VDC. Therefore, in order to obtain the most representative sample, households from each of the nine wards had to be included. To calculate the number of households that had to be interviewed in each ward, we used a probability proportional to size sampling, the measure of size being the number of households living in the ward. The number of households that had to be interviewed in a ward was thus likely to increase with its population size. Consequently, the probability of selection of a household was increasing with the ward's population size.[29] We used the most recent information on population size, that was either from local data recorded by VDCs' administrative bureau, or from the 2011 national census. This first step in the households selection process had the advantage of reducing logistic and transportation costs, while generating a good representativeness. Indeed, less populated wards were often located remotely and were difficult to access. Since less households had to be interviewed in those wards, less resources had to be allocated to get there. It is noteworthy that certain wards had to be excluded from the sample because of the difficulty of access.

Second, households surveyed were identified using a random systematic sampling. This method involves drawing a first household randomly, and selecting the others following a regular interval based on their geographic location. For instance, in a ward composed of 100 households, in which ten households must be surveyed (as per the first step described above), the interval is $\frac{100}{10} = 10$. A first household to be interviewed is thus identified randomly, then ten households (or residences) are counted. The tenth is the next to be surveyed. This method was used as it permitted to obtain a probabilistic sample, in the absence of a household sampling frame.[30] Random systematic sampling attributes an equal selection probability to all households that belong to a same ward. Therefore, the selection probability of household i, conditional on the selection of its VDC of residence j, is calculated by:

$$\pi_{i|j} = \left(W\frac{N_i^{(w)}}{N_j}\right) \times \left(\frac{n_i^{(w)}}{N_i^{(w)}}\right) \quad (9)$$

where W is the total number of wards in the VDC, excluding the ones that were not considered because of the difficulty of access, $N_i^{(w)}$ is the total number of households in ward w and $n_i^{(w)}$ is the

[28] Except in the VDC of Lete, where a census was conducted due to its small population size.

[29] Technically, to complete this step, we programmed in Stata a number associated with each ward. Each number was replicated $N_i^{(w)}$ times, $N_i^{(w)}$ being the number of households in ward w. Then, we conducted a simple random sampling to draw as many numbers as the number of households that had to be interviewed in the VDC. The number of drawn numbers associated with each ward determined the number of households in the ward that had to be interviewed.

[30] We tried to obtain a list of households in each ward in order to conduct a simple random sampling, but such lists were not available in most VDCs.

Table 6
Database structure summary.

	Selected VDCs	Number of wards included in the sample	Number of households surveyed
Annapurna C.A.	Lete	8	149
	Narchyang	6	117
	Lumle	6	120
	Ghandruk	7	150
Langtang N.P.	Dhunche	8	174
	Syafru	7	161
	Laharepauwa	5	156
Chitwan N.P.B.Z.	Meghauly	9	177
	Dibyapuri	6	179
	Bachhauli	9	180
Total		71	1,563

number of selected households in ward w. The first term in the parenthesis on the right side of the equality is thus the selection probability associated with the calculation of the per-ward household number that must be surveyed. The second term in parenthesis is the selection probability associated with the systematic sampling within the ward.

Appendix C. Database structure summary

Table 6

Appendix D. The multilevel model

The multilevel model can be defined according to the general form:

$$Y = X\beta + ZU + \epsilon \qquad \epsilon \sim \mathcal{N}(0, \sigma^2_\epsilon) \tag{10}$$

where the dependent variable Y is a $n \times 1$ vector, n being the number of observations at the inferior level, X is a $n \times p$ matrix of independent variables, β is a $p \times 1$ vector of unknown parameters, called "fixed effects",[31] Z is a $n \times q$ matrix of independent variables, and U is a $q \times 1$ vector of random effects. The vector $\epsilon, n \times 1$, is the individual random error that we suppose normally distributed around 0 with constant variance. The fixed effect, β, is analogous to coefficients estimated with an OLS method. As for the random effect U, it is not directly estimated but characterized by its variance. Therefore, assuming that ϵ and U are orthogonal, the model variance structure is defined as:

$$Var\begin{pmatrix} U \\ \epsilon \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & \sigma^2_\epsilon \end{pmatrix} \tag{11}$$

where Σ is the variance–covariance matrix of the random effects vector U.

Appendix E. Estimation approach, scaling factors and simulations

We estimate the model using a pseudo-maximum likelihood approach. This method is recommended when including sample weights in the model is needed (Asparouhov, 2006; Rabe-Hesketh & Skrondal, 2006; Jia et al., 2011). Including sample weights to estimate a one-level regression model is a common procedure in applied microeconometrics. However, theoretical and empirical works related to sample weights inclusion in multilevel models are still scarce and there is no consensus on which method produces the most reliable results[32] (Asparouhov, 2006; Carle, 2009). Nevertheless, two issues related to the use of sample weights in multilevel models stand out. First, if the sample design is multistage and observations are correlated, including only one vector of weights proportional to the inverse of level-1 units' total probability of selection in the likelihood function will produce a bias (Pfeffermann et al., 1998). Several authors thus recommend to calculate a vector of weights for each unit (each stage) and to include them in the model separately (e.g. Pfeffermann et al., 1998; Korn & Graubard, 2003; Asparouhov, 2006; Rabe-Hesketh & Skrondal, 2006). In this article, we use the estimation method developed by Rabe-Hesketh and Skrondal, 2006, which includes sample weights in the likelihood function based on this approach.

Let the model:

$$y_{ij} = x_{ij}\beta + z_{ij}u_j + \epsilon_{ij} \qquad Var\begin{pmatrix} U \\ \epsilon \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & \sigma^2 \end{pmatrix} \tag{12}$$

as defined in (10) and (11), with i the level-1 unit, and j the level-2 unit.

Let $f(y_{ij}|u_j, \beta, \sigma^2)$ the marginal density of y, conditional on estimated parameters β, σ^2 and on random effect u_j. Since y_{ij} and u_j are not independent, let us use the joint density:

$$f(y_{ij}, u_j|\beta, \sigma^2, \Sigma) = f(y_{ij}|u_j, \beta, \sigma^2) f(u_j|\Sigma) \tag{13}$$

and integrate to obtain the marginal density of y, unconditional on random effects:

$$f(y_{ij}|\beta, \sigma^2, \Sigma) = \int f(y_{ij}|u_j, \beta, \sigma^2) f(u_j|\Sigma) du_j \tag{14}$$

Let J the number of level-2 units (cluster) and n_j the number of per-cluster level-1 units. Since

$$y_{ij} \perp\!\!\!\perp y_{i'j} \quad \forall i, i' \in j \qquad \text{and} \qquad u_j \perp\!\!\!\perp u_{j'} \quad \forall j, j'$$

then the joint density of observations of the whole distribution is:

$$f(y|\beta, \sigma^2, \Sigma) = \prod_{j=1}^{J} \int \prod_{i=1}^{n_j} f(y_{ij}|u_j, \beta, \sigma^2) f(u_j|\Sigma) du_j \tag{15}$$

Therefore, the Likelihood function is $\mathcal{L}(\beta, \sigma^2, \Sigma|y) = f(y|\beta, \sigma^2, \Sigma)$. Let take the logarithm:

$$l(\beta, \sigma^2, \Sigma|y) = \log\left[\prod_{j=1}^{J} \int \prod_{i=1}^{n_j} f(y_{ij}|u_j, \beta, \sigma^2) f(u_j|\Sigma) du_j\right] \tag{16}$$

Let redefine:

$$\prod_{i=1}^{n_j} f(y_{ij}|u_j, \beta, \sigma^2) = \exp\left[\sum_{i=1}^{n_j} \log f(y_{ij}|u_j, \beta, \sigma^2)\right] \tag{17}$$

By introducing (17) in (16), we obtain:

$$l(\beta, \sigma^2, \Sigma|y) = \sum_{j=1}^{J} \log\left(\int \exp\left[\sum_{i=1}^{n_j} \log f(y_{ij}|u_j, \beta, \sigma^2)\right] f(u_j|\Sigma) du_j\right) \tag{18}$$

Let ω_j, the weight associated with cluster j, corresponding to the inverse of its selection probability and $\omega_{i|j}$, the weight associated with unit i in cluster j, corresponding to the inverse of its selection probability, conditional on the section of cluster j. By including sample weights in (18) as in Rabe-Hesketh and Skrondal (2006), we obtain the log-likelihood function:

[31] In multilevel modeling, a fixed effect refers to a regression coefficient that does not vary between the superior level units.

[32] See for instance Pfeffermann et al. (1998), Korn and Graubard (2003), Kovacevic and Rai (2003), Grilli and Pratesi (2004), Rabe-Hesketh and Skrondal (2006).

$$l(\beta,\sigma^2,\Sigma|y)=\sum_{j=1}^{J}\omega_j\log\left(\int\exp\left[\sum_{i=1}^{n_j}\omega_{i|j}\log f\left(y_{ij}|u_j,\beta,\sigma^2\right)\right]f\left(u_j|\Sigma\right)du_j\right) \tag{19}$$

The log-likelihood function that is estimated, $l(\beta,\sigma^2,\Sigma|y)$ is thus composed of a weighed sum of J independent log-likelihood functions.

The second issue related to the use of sample weights in a multilevel model is that simulation works show that level-1 units' sample weights generate an overestimation of the variance of random effects (e.g. Pfeffermann et al., 1998; Rabe-Hesketh & Skrondal, 2006; Jia et al., 2011). Rabe-Hesketh and Skrondal (2006) explain this problem analytically by showing that sample weights artificially increase cluster sizes, which produces an upward bias of the inter-group variance. This inter-group variance overestimation is then mistakenly attributed to the variance of random effects. In order to reduce the bias, it is recommended to transform level-1 units' sample weights with a scaling method.

Scaling consists of multiplying the weights vector by a scaling factor. Different scaling factors have been suggested and tested (e.g. Pfeffermann et al., 1998; Asparouhov, 2006; Korn & Graubard, 2003; Rabe-Hesketh & Skrondal, 2006; Jia et al., 2011), but there is no consensus on which one produces the most reliable estimates. In the literature, two scaling methods have retained attention: "method 1" and "method 2" of Pfeffermann et al. (1998).[33]

Let $\omega_{i|j}$ be the weight associated with unit i, conditional on the selection of unit j, where i is the level-1 unit and j is the level-2 unit.

1. Method 1 of Pfeffermann et al. (1998)
   The scaling factor λ_j^1 is such that the sum of weights associated with the n_j observations that belong to cluster j is equal to the "effective" size of the cluster.[34] "Method 1" adjusted weight, $\omega_{i|j}^{(1)}$, is calculated by:

$$\omega_{i|j}^{(1)}=\lambda_j^1\omega_{i|j}=\omega_{i|j}\frac{\sum_{i=1}^{n_j}\omega_{i|j}}{\sum_{i=1}^{n_j}\omega_{i|j}^2} \tag{20}$$

2. Method 2 of Pfeffermann et al. (1998)
   The scaling factor λ_j^2 is such that the sum of weights associated with the n_j observations that belong to cluster j is equal to the cluster j sample size. The "method 2" adjusted weight, $\omega_{i|j}^{(2)}$, is calculated by:

$$\omega_{i|j}^{(2)}=\lambda_j^2\omega_{i|j}=\omega_{i|j}\frac{n_j}{\sum_{i=1}^{n_j}\omega_{i|j}} \tag{21}$$

However, actual knowledge on sample weights inclusion in multilevel models is not sufficiently developed to determine which scaling factor is the most robust, and the bias size can depend on the sample design as well as on which parameter is estimated (Snijders & Bosker, 2012). Further, in the literature, simulations that aim at evaluating sample weights and scaling effects on estimates consider mainly the bias associated with the variance of random effects. However, in this analysis, we are mostly concerned with the reliability of regression coefficients. Therefore, published results are not sufficient to guide our methodological choices. In this context, we conduct a simulation that reproduces our sample design and database structure.

The simulation goal is to verify the effect of sample weights and different scaling factors on estimated parameters bias, given the sample design and the database structure. Parametrization must thus allow reproducing the database structure as accurately as possible, in particular characteristics that are likely to generate a bias. According to Pfeffermann et al. (1998), regression coefficients will be consistent if the level-2 number of units is sufficiently large, given the random effects and residuals variance. In addition, according to Jia et al. (2011) drawing on Pfeffermann et al. (1998), Grilli and Pratesi (2004), Asparouhov (2006), three different factors contribute to generating a random effects variance bias:

1. Cluster size: the smaller the cluster, the higher the bias;
2. Intraclass correlation: the smaller the intraclass correlation, the higher the bias;
3. Weights informativeness[35]: the more informative the weights, the higher the bias.

Therefore, in addition to the sample design, the parametrization must reproduce cluster sizes, the intraclass correlation and the weights informativeness that characterize the database. The dependent variable y is calculated such that $y_{ij}=\beta_0+\beta_{x_{ij}}x_{ij}+\beta_{x_j}x_j+u_j+\epsilon_{ij}$, where x_{ij} and x_j are respectively household-level and ward-level explanatory variables, u_j is the random effect, and ϵ_{ij} is the individual error term.

In order to reproduce the sample design as well as the clusters size, we use the real sample and replicate observations using sample weights so that the number of observations equals the real population size. Then we proceed with a random draw using the same probabilities of selection that were used in the survey, so that the simulated sample equals the size of the real sample.

To reproduce the intraclass correlation, we simulate a vector of random effects u and a vector of residuals e so that $u\sim\mathcal{N}(0,0,1)$ and $e\sim\mathcal{N}(0,0,4)$. This parametrization allows for replicating the first and second moments of the residuals and random effects vector that are estimated using model (22). The intraclass correlation calculated with these simulated parameters is 0.2, which tends towards the ICC calculated with the results of (22).

Two explanatory variables are integrated in the simulated model. The first, x_{ij}, is a household-level variable while the second, x_j, is measured at the ward-level. We use these two variables since an estimator's performance can vary between coefficients associated with different levels of analysis (Rabe-Hesketh & Skrondal, 2006). It is noteworthy that these variables are not simulated but built using the real database.

Dependent variable y is then calculated so that $y_{ij}=1+x_{ij}+x_j+u_j+e_{ij}$, which implies coefficient values of $\beta_0=\beta_{x_{ij}}=\beta_{x_j}=1$.

Finally, weight informativeness is difficult to reproduce as it is difficult to measure. Therefore, since the moments of our simulated random effects and residuals are close to the estimated ones, and since we use sample weights and explanatory variables from the real sample, we assume that weight informativeness in the simulated sample is similar to the one in the real sample.

We conduct three simulations: (M0) with sample weights and no scaling; (M1) with sample weights and scaling method 1; (M2) with sample weights and scaling method 2. Results are presented in Table 7.

Both scaling methods (M1 and M2) generate identical results. Estimates of $\beta_{x_{ij}}$ and β_{x_j}, with and without scaling, converge towards their true value, relative bias being very small and varying

[33] For theoretical justification of these methods see Pfeffermann et al. (1998) or Rabe-Hesketh and Skrondal (2006).

[34] The "effective" size is defined in Potthoff, Woodbury, and Manton (1992).

[35] Weights informativeness, as defined in Pfeffermann (1993), measures the dependence between sample weights and the dependent variable.

Table 7
Simulation results.

Parameter	M0		M1		M2	
	Estimate	Rel. bias	Estimate	Rel. bias	Estimate	Rel. bias
β_0	1.0003	0.0003	1.0010	0.0010	1.0010	0.0010
$\beta_{x_{ij}}$	1.0003	0.0003	0.9997	−0.0003	0.9997	−0.0003
β_{x_j}	1.0006	0.0006	0.9993	−0.0007	0.9993	−0.0007
σ_u^2	0.1274	0.2745	0.0931	−0.0690	0.0931	−0.0690
σ_ϵ^2	0.3890	−0.0275	0.3994	−0.0015	0.3994	−0.0015

5,000 iterations. Pseudo maximum likelihood estimation. Rel. bias is the relative bias. True values: $\beta_0 = 1, \beta_{x_{ij}} = 1, \beta_{x_j} = 1, \sigma_u^2 = 0.10, \sigma_\epsilon^2 = 0.40$. σ_u^2 is the variance of u. σ_ϵ^2 is the variance of ϵ.

between -0.0007 and 0.0006. The relative bias calculated for the random effect variance, σ_u^2, is more important but consistent with the literature. Indeed, the estimation without scaling overestimates the variance by 27.45%, while the estimation with scaling underestimates it by 6.90%. The estimation with scaling thus generates a more reliable result.

A Wald test confirms that using or not a scaling factor does not affect significantly regression coefficients. Therefore, we will estimate the model with and without scaling. If the model is well specified, regression coefficients should be statistically equal with and without scaling, which will be verified with a Wald test. Since both scaling methods generate identical results, we will only use Method 1. Finally, the bias associated with random effects variance will have to be taken into account in the results interpretation.

Appendix F. Random intercept empty model

The empty model is defined as:

$$y_{ij} = \gamma_{00} + u_j + \epsilon_{ij} \tag{22}$$

where y_{ij} is the welfare of household i in ward j, γ_{00} is an intercept, u_j is a random effect, and ϵ_{ij} is an individual error term. In this model, γ_{00} is interpreted as the average welfare in the population, and u_j captures characteristics that are common to households in a same ward. Therefore, $(\gamma_{00} + u_j)$ is an estimate of the average welfare in ward j, while the welfare of each household i in ward j deviates from this mean by ϵ_{ij}. The average welfare in each ward varies randomly according to an inter-group variance, σ_u^2, and the welfare of households in a same ward varies randomly according to an intra-group variance σ_ϵ^2. Results with and without scaling are presented in Table 8.

In order to measure the between-ward heterogeneity, we calculate the intraclass correlation (ICC). ICC measures the dependence between observations that belong to a same cluster. In this analysis, it thus measures how similar households in a same ward are.

Table 8
Random intercept empty model results.

	Consumption expenditures	
Scaling	No	Yes
Fixed effect		
Intercept	11.564*** (0.122)	11.567*** (0.127)
Random effects		
σ_u^2	0.157 (0.028)	0.133 (0.027)
σ_ϵ^2	0.419 (0.023)	0.466 (0.052)
ICC	0.273	0.222
Observations	1,563	1,563

***1% significant. Robust standard deviations in parenthesis. Consumption expenditures are in logarithm and expressed per adult equivalent.

Formally, assuming error terms are independent, total variance σ^2 is expressed as the sum of two terms such that $\sigma^2 = \sigma_u^2 + \sigma_\epsilon^2$. ICC is thus defined by:

$$ICC = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_\epsilon^2}$$

ICC calculated with unscaled (scaled) estimates equals 0.273 (0.222). Therefore, around a quarter of total welfare variance in the population is explained by characteristics that are common to households belonging to a same ward. Assuming that random effects are normally distributed, a test of Fisher allows to reject the null hypothesis that ICC equals 0. Indeed, the statistic following a Fisher law $F(70, 1492)$, calculated using unscaled (scaled) estimates, is of 5.015 (3.812). We thus reject the null hypothesis at 1%. This result confirms the existence of between-ward heterogeneity. Using a multilevel model is thus appropriate for this analysis.

Appendix G. Intra-group and inter-group regression coefficients

When estimating a multilevel model, it is useful to distinguish between intra-group and inter-group regression coefficients associated with level-1 variables. Indeed, when observations in a same group (cluster) are correlated, level-1 explanatory variables are likely to affect the dependent variable through two potentially distinct and independent effects: (1) an individual or intra-group effect and (2) a cluster or inter-group effect. Intra-group regression coefficients thus measure average individual effects of explanatory variables on the dependent variable for observations in a same cluster. As for inter-group coefficients, they capture intra-cluster average effects of explanatory variables, on the intra-cluster mean of the dependent variable (Snijders & Bosker, 2012). Distinguishing these two effects thus allows obtaining more specific results. Different methods can be used in order to calculate intra-group and inter-group coefficients in a regression model.[36] In this article, we estimate the inter-group coefficient for a level-1 variable by including in the model the variable intra-cluster mean. Then, we estimate the intra-group coefficient by substituting the explanatory variable by its value centered with regard to its intra-cluster mean.

Formally, let us suppose a two-level model, including one explanatory variable x_{ij} and its intra-cluster mean $\bar{x}_{.j}$. To estimate intra-group and inter-group coefficients, the model is:

$$y_{ij} = \gamma_{00} + \gamma_{10}(x_{ij} - \bar{x}_{.j}) + \gamma_{01}\bar{x}_{.j} + u_{0j} + \epsilon_{ij} \tag{23}$$

where γ_{10} captures the intra-group effect and measures the average effect of x_{ij} on y_{ij}, for observations in ward j, and γ_{01} captures the inter-group effect and measures the mean of x_{ij} average effect on

[36] For more details, see for instance Snijders and Bosker (2012).

y_{ij}, in ward j. Let us mention that (23) is statistically equivalent to the model

$$y_{ij} = \tilde{\gamma}_{00} + \tilde{\gamma}_{10}x_{ij} + \tilde{\gamma}_{01}\bar{x}_{.j} + u_{0j} + \epsilon_{ij}$$

in which x_{ij} is not centered with regard to its intra-cluster mean. Indeed, it can be shown with few manipulations that the inter-group coefficient $\gamma_{01} = \tilde{\gamma}_{10} + \tilde{\gamma}_{01}$, and that the intra-group coefficient $\gamma_{10} = \tilde{\gamma}_{10}$. However, Snijders and Bosker (2012) recommend to use centered variables as the estimation of inter-group coefficients is then more direct, and estimates are easier to interpret. Furthermore, since x_{ij} and $\bar{x}_{.j}$ are likely to be correlated, centering x_{ij} allows eliminating collinearity (Angelson et al., 2014). Indeed, level-1 variables that are centered with regard to their intra-cluster mean are orthogonal to level-2 variables (Paccagnella, 2006). We thus use this procedure recommended by Snijders and Bosker (2012) to estimate intra-group and inter-group coefficients.

Appendix H. Relationships between control variables and household welfare

In terms of relationships between control variables and welfare, we find a negative link between the household size and welfare. The share of household members aged of less than 15 and more than 60 years old is also negatively related to consumption. In addition, households that belong to the caste of Dalit have a lower welfare, which has also been found by Bennett et al., 2008. Regarding human capital, results show that a higher welfare is associated with a higher level of education in the household. As for the employment, we find that the share of household that work in the farm sector is negatively linked to welfare while the share of household that is self-employed in a sector other than farming and tourism is positively related to consumption. This result is not surprising since according to the Nepal Labour Force Survey conducted in 2008, the agricultural sector employed 73.9% of the labor force (ILO, 2017), and 64% of them are engaged in subsistence farming (CBS, 2008). Receiving remittances is associated with a higher welfare. As for the physical capital owned by the household, results suggest that both the size of land and the value of the residence are positively related to consumption. Access to infrastructures is also associated with higher welfare. Finally, having collected firewood in the forest is negatively related to welfare, which suggests that poor households rely more on natural resource collection. This is consistent with the hypothesis that poorer households have a higher tendency to use forest resources as a source of energy while richer households use other types of sources such as kerosene or gas (Baland et al., 2010).

Appendix I. Cook's distance test results

Let p the number of fixed parameters, q the number of random parameters, $\hat{\beta}$ the estimated fixed coefficients vector, $\hat{U}$ the estimated random parameters vector, $\hat{\Sigma}_F$ the estimation of the fixed parameters covariance matrix, and $\hat{\Sigma}_A$ the estimation of the random parameters covariance matrix. Index $-j$ indicates that ward j is removed from the estimation. The measure of ward j's influence on fixed parameters is calculated by

$$C_j^F = \frac{1}{p}\left(\hat{\beta} - \hat{\beta}_{-j}\right)^T \hat{\Sigma}_{F(-j)}^{-1}\left(\hat{\beta} - \hat{\beta}_{-j}\right) \tag{24}$$

Likewise, the measure of ward j's influence on random parameters is calculated by

$$C_j^A = \frac{1}{q}\left(\hat{U} - \hat{U}_{-j}\right)^T \hat{\Sigma}_{A(-j)}^{-1}\left(\hat{U} - \hat{U}_{-j}\right) \tag{25}$$

Table 9
Cook's distance test results.

Ward ID	C_j^F	C_j^A	C_j
1	2.825	0.046	2.612
2	2.003	0.010	1.850
3	0.916	0.041	0.849
4	0.577	0.025	0.535
5	0.549	0.023	0.508
6	0.504	0.033	0.468
7	0.456	0.014	0.422
8	0.346	0.004	0.320
9	0.285	0.022	0.265
10	0.226	0.709	0.263
11	0.271	0.001	0.250
12	0.244	0.019	0.226
13	0.209	0.024	0.195
14	0.201	0.119	0.194
15	0.207	0.039	0.194
16	0.190	0.063	0.180
17	0.188	0.071	0.179
18	0.160	0.010	0.148
19	0.157	0.043	0.148
20	0.114	0.016	0.107
21	0.102	0.091	0.101
22	0.092	0.042	0.088
23	0.083	0.126	0.086
24	0.086	0.013	0.081
25	0.077	0.017	0.073
26	0.078	0.007	0.073
27	0.071	0.006	0.066
28	0.060	0.041	0.058
29	0.057	0.049	0.057
30	0.024	0.061	0.027
31	0.012	0.088	0.018

Cutoff value = 0.06.

Finally, the ward j's total influence on the set of estimated parameters is calculated by

$$C_j = \frac{1}{p+q}\left(pC_j^F + qC_j^A\right) \tag{26}$$

C_j^F and C_j^A are compared to the cutoff value proposed by Belsley, Kuh, and Welsch (1980), which is equal to $\frac{4}{J}$, where J is the total number of wards. Wards for which one of these measures is superior to the cutoff value are considered as having an important influence on estimations. Snijders and Bosker (2012) explain that if the model is well specified and that explanatory variables are approximately randomly distributed between groups, the measure of a group's influence should be roughly proportional to its size in order not to generate a bias. Therefore, a small ward, having a measure that is superior to the cutoff value, would be likely to bias results.

Results, obtained using non-scaled estimations, are presented in Table 9. Among the 71 wards of the sample, 31 have a measure superior to the cutoff value of Belsley et al., 1980. In order to identify wards associated with a measure that is influent but not proportional to the ward size, we calculate a ratio between the Cook's measure and the ward size for the 31 wards having a measure superior to the cutoff value. A constant ratio would indicate a measure proportional to the size of influent wards. The calculated ratios have a mean value of 0.00009 and a standard deviation of 0.0001583. In total, the ratios of 4 influent wards out of the 31 who have a measure superior to the cutoff value are superior to the mean by more than one standard deviation. In order to check their influence on the variables of interest, we estimate the model eliminating these 4 wards, one after the other. Table 10 contains the estimated coefficients associated with variables of interest for these 4 estimations. M0 refers to the estimation with the complete

Table 10
Variables of interest, for complete sample (M0) and subsamples (M1–M4).

	M0	M1	M2	M3	M4
Tourism involvement – wage job	−0.012	−0.013	−0.048	−0.012	−0.011
Tourism involvement – self-employed	0.524***	0.553***	0.520***	0.523***	0.526***
Environmental restriction	−0.002	−0.002	−0.002	−0.001	−0.003
Tourism *ward* – wage	−0.367	−0.174	0.060	−0.505	−0.554
Tourism *ward* – self-employed	1.033**	0.784**	1.070**	1.244**	1.367***

***1% significant. **5% significant. *10% significant.

sample, and models M1–M4 refer to estimations eliminating one of the influent wards.

We observe that eliminating an influent ward does not modify the sign or the significance of the variables of interest. Further, coefficients associated with significant variables remain in the confidence interval estimated with the complete sample.[37] Therefore, this test confirms that results are robust with regard to the cluster effect as they that are not generated by one or more wards too influential.

[37] For $tour^{self}$, the confidence interval is [0.30; 0.70]. For $tourward^{self}$, the confidence interval is [0.27; 1.78].

References

Acharya, B., & Halpenny, E. (2013). Homestays as an alternative tourism product for sustainable community development: A case study of women-managed tourism product in rural Nepal. *Tourism Planning and Development, 10*(4), 367–387.

Adams, W., Aveling, R., Brockington, D., Dickson, B., Elliott, J., Hutton, J., Roe, D., et al. (2004). Biodiversity conservation and the eradication of poverty. *Science, 36*, 1146–1148.

Government of Nepal. (2015). *Chitwan National Park and its Buffer Zone Management Plan 2013–2017*. Chitwan National Park Office.

ADB. (2016). Poverty in Nepal. http://www.adb.org/countries/nepal/poverty..

Adhikari, B. (2005). Poverty, property rights and collective action: Understanding the distributive aspects of common property resources management. *Environment and Development Economics, 10*, 7–31.

Andam, K., Ferraro, P., Sims, K., Healy, A., & Holland, W. (2010). Protected areas reduced poverty in Costa Rica and Thailand. *Proceedings of the National Academy of Sciences of the United States of America, 107*(22), 9996–10001.

Angelson, A., Jagger, P., Babigumira, R., Belcher, B., Hogarth, N., Bauch, S., Börner, J., Smith-Hall, C., & Wunder, S. (2014). Environmental income and rural livelihoods: A global-comparative analysis. *World Development, 64*, S12–S28.

Anthon, S., Lund, J. F., & Helles, F. (2008). Targeting the poor: Taxation of marketed forest products in developing countries. *Journal of Forest Economics, 14*, 197–224.

Asparouhov, T. (2006). General multi-level modeling with sampling weights. *Communication in statistics - Theory and methods, 35*, 439–460.

Baland, J., Bardhan, P., Das, S., Mookherjee, D., & Sarkar, R. (2010). The environmental impact of poverty: Evidence from firewood collection in rural Nepal. *Economic Development and Cultural Change, 59*(1), 23–61.

Bandyopadhyay, S., & Tembo, G. (2010). Household consumption and natural resource management around national parks in Zambia. *Journal of Natural Resources Policy Research, 2*(1), 39–55.

Baral, N., Stern, M. J., & Heinen, J. T. (2007). Integrated conservation and development project life cycles in the Annapurna Conservation Area, Nepal: Is development overpowering conservation? *Biodiversity Conservation*.

Basnett, Y., Henley, G., Howell, J., Jones, H., Lemma, A., and Pandey, P. (2014). Structural economic transformation in Nepal. A diagnostic study submitted to DFID Nepal. https://www.odi.org/sites/odi.org.uk/files/odi-assets/publications-opinion-files/9019.pdf..

Belsley, D., Kuh, E., & Welsch, R. (1980). *Regression diagnostics: Identifying influential data and sources of collinearity*. New York: John Wiley.

Bennett, L., Dahal, D., & Govindasamy, P. (2008). *Caste, ethnic and regional identity in Nepal: Further analysis of the 2006 Nepal demographic and health survey*. Calverton, Maryland, USA: Macro International Inc.

Bhatta, S., & Sharma, S. (2006). The determinants and consequences of chronic and transient poverty in Nepal. *CPRC Working, paper*, 66.

Bhattarai, B., Wright, W., Poudel, B. S., Aryal, A., Yadav, B., & Wagle, R. (2017). Shifting paradigms for Nepal's protected areas: history, challenges and relationships. *Journal of Mountain Science, 14*(5), 964–979.

Brockington, D., & Wilkie, D. (2015). Protected areas and poverty. *Philosophical Transactions of the Royal Society B, 370*(20140271), 1–6. https://doi.org/10.1098/rstb.2014.0271.

Budhathoki, P. (2005). Landscape conservation initiatives in Nepal: Opportunities and challenge. https://portals.iucn.org/library/efiles/html/PA-protected-landscape-approach/PartII-Section 6.html..

Butler, R. (1980). The concept of a tourist area cycle of evolution: Implications for a management of resources. *Canadian Geographer, 24*(1), 5–12.

Cameron, C., & Miller, D. (2010). *Robust inference with clustered data. Working paper no. 10.7* (no). University of California, Department of Economics.

Canavire-Bacarreza, G., & Hanauer, M. (2013). Estimating the impacts of Bolivia's protected areas on poverty. *World Development, 41*, 265–285.

Carle, A. (2009). Fitting multilevel models in complex survey data with design weights: Recommendations. *BMC Medical Research Methodology, 9*(1), 1.

CBS. (2008). Report on the Nepal Labour Force Survey. http://cbs.gov.np/image/data/Surveys/2015/NLFS-2008.

CBS. (2011). Nepal living standard survey. Statistical Report..

CBS. (2012). National population census 2011..

Chok, S., Macbeth, J., & Warren, C. (2007). Tourism as a tool for poverty alleviation: A critical analysis of pro-poor tourism and implications for sustainability. *Current Issues in Tourism, 10*(2), 144–165.

Coad, L., Campbell, A., Miles, L., and Humphries, K. (2008). The costs and benefits of forest protected areas for local livelihoods: A review of the current literature. Working Paper. UNEP World Conservation Monitoring Centre, Cambridge, U.K..

Deaton, A. (1997). *The analysis of household surveys: A microeconometric approach to development policy*. The World Bank.

Deaton, A. and Zaidi, S. (2002). Guidelines for constructing consumption aggregates for welfare analysis. The World Bank, Washington D.C. LSMS working paper. Number 135..

den Braber, B., Evans, K. L., & Oldekop, J. A. (2018). Impact of protected areas on poverty, extreme poverty, and inequality in nepal. *Conservation Letters, 11* (e12576), 1–9.

Dhakal, B., & Thapa, B. (2015). Buffer Zone Management Issues in Chitwan National Park, Nepal: A Case Study of Kolhuwa Village Development Committee. *Parks, 21*(2), 63–72.

DNPWC. (2014). Protected areas. http://www.dnpwc.gov.np/..

DNPWC. (2018). Protected areas. http://www.dnpwc.gov.np/..

Dudley, N., Mansourian, S., Stolton, S., and Suksuwan, S. (2008). *Safety Net. Protected areas and poverty reduction*. Technical report, World Wide Fund for Nature and Equilibrium. ISBN: 978-2-88085-279-5..

England, L., & Albrecht, S. (1984). Boomtowns and social disruption. *Rural Sociology, 49*(2), 230–246.

Eugenio, M., Morales, N., & Scarpa, R. (2004). Tourism and economic growth in Latin American countries: A panel data approach. *Natural Resources Management*, 1–20.

Ferraro, P., & Hanauer, M. (2011). Protecting ecosystems and alleviating poverty with parks and reserves: Win-win or tradeoffs? *Environmental and Resource Economics, 48*, 269–286.

Ferraro, P., & Hanauer, M. (2014). Quantifying causal mechanisms to determine how protected areas affect poverty through changes in ecosystem services and infrastructure. *Proceedings of the National Academy of Science of the United States, 111*, 4332–4337.

Ferraro, P., Hanauer, M., & Sims, K. (2011). Conditions associated with protected area success in conservation and poverty reduction. *Proceedings of the National Academy of Sciences of the United States of America, 108*(34), 13913–13918.

Forsyth, T., Leach, M., and Scoones, I. (1998). Poverty and environment: Priorities for research and policy. http://eprints.lse.ac.uk/4772/1/Poverty_and_environment-priorities_for_research_and_study.pdf..

Goodwin, H. (2006). Measuring and reporting the impact of tourism on poverty Cutting edge research in tourism – New directions, challenges and applications. In *School of Management* (pp. juin.). UK: University of Surrey.

Goodwin, H., & Roe, D. (2001). Tourism, livelihoods and protected areas: Opportunities for fair-trade tourism in and around national parks. *International journal of tourism research, 3*, 377–391.

Government of Nepal. (2014). Langtang National Park. http://www.langtangnationalpark.gov.np/..

Grieg-Gran, M., Porras, I., & Wunder, S. (2005). How can market mechanisms for forest environmental services help the poor? Preliminary lessons from Latin America. *World Development, 33*(9), 1511–1527.

Grilli, L., & Pratesi, M. (2004). Weighted estimation in multilevel ordinal and binary models in the presence of informative sampling designs. *Survey Methodology, 30* (1), 93–104.

Heinen, J., & Shrestha, S. (2006). Evolving policies for conservation: An historical profile of the protected area system of Nepal. *Journal of Environmental Planning and Management, 49*(1), 41–58.

Hox, J. (1998). *Classification, data analysis, and data highways, chapter Multilevel modeling: When and why?* Springer Verlag.
Hox, J. (2010). *Multilevel analysis. Techniques and applications*. Great-Britain: Routledge. second edition.
Hunt, C., Durham, W., Driscoll, L., & Honey, M. (2014). Can ecotourism deliver real economic, social, and environmental benefits? A study of the Osa Peninsula, Costa Rica. *Journal of Sustainable Tourism, 23*(3), 339–357.
IFAD. (2013). *Enabling poor rural people to overcome poverty in Nepal.* https://www.ifad.org/documents/10180/c3f05a7f-627b-40a6-8bce-c3330c9849dc..
IFAD. (2014). *Rural poverty in Nepal.* http://www.ruralpovertyportal.org/country/home/tags/nepal..
ILO. (2017). *Nepal labour market update.* https://www.ilo.org/wcmsp5/groups/public/—asia/—ro-bangkok/—ilo-kathmandu/documents/publication/wcms_543497.pdf..
IPPG. (2019). *Working for the safety of the mountain porter.* http://www.ippg.net/..
IUCN. (2016). Protected Areas Categories. https://www.iucn.org/theme/protected-areas/about/protected-areas-categories..
Jia, Y., Stokes, L., Harris, I., & Wang, Y. (2011). Performance of random effects model estimators under complex sampling designs. *Journal of Educational and Behavioral Statistics, 36*(1), 6–32.
Keiter, R. (1995). Preserving Nepal's National Parks: Law and Conservation in the Developing World. *Ecology Law Quarterly, 22*(3), 591–675.
Korn, E., & Graubard, B. (2003). Estimating variance components by using survey data. *Journal of the Royal Statistical Society. Series B, 65*(1), 175–190.
Kovacevic, M., & Rai, S. (2003). A pseudo maximum likelihood approach to multilevel modelling of survey data. Communications in statistics. *Theory and Methods, 32*(1), 103–121.
Lamichhane, B. R., Persoon, G., Leirs, H., Musters, C., Subedi, N., Gairhe, K., et al. (2017). Are conflict-causing tigers different? Another perspective for understanding human-tiger conflict in Chitwan National Park Nepal. *Global Ecology and Conservation, 11*, 177–187.
Lokshin, M., Bontch-Osmolovski, M., & Glinskaya, E. (2010). Work-related migration and poverty reduction in Nepal. *Review of Development Economics, 14*(2), 323–332.
Maas, C., & Hox, J. (2005). Sufficient sample sizes for multilevel modeling. *Methodology, 1*(3), 86–92.
Mbaiwa, J. (2015). Ecotourism in Bostwana: 30 years later. *Journal of Ecotourism, 14*(2–3), 204–222.
Möhring, K. and Schmidt, A. (2012). *Multi level tools. Influential cases in multi level modeling.* http://www.stata.com/meeting/germany12/abstracts/desug12_moehring.pdf..
Mink, S. D. (1993). Poverty, population and the environment. *World Bank discussion, paper*, 189.
MTCA. (2013). Nepal tourism statistics 2012..
Nagendra, H., & Gokhale, Y. (2008). Management regimes, property rights and forest biodiversity in Nepal and India. *Environmental Management, 49*, 719–733.
Naughton-Treves, L., Alex-Garcia, J., & Chapman, C. (2011). Lessons about parks and poverty from a decade of forest loss and economic growth around Kibale National Park, Uganda. *PNAS, 108*(34), 13919–13924.
Nepal, K. (2000). Tourism in protected areas. The Nepalese Himalaya. *Annals of Tourism Research, 27*(3), 661–681.
Neto, F. (2003). A new approach to sustainable tourism development: Moving beyond environmental protection. *Natural Resources Forum, 27*, 212–222.
NTNC. (2019). *Annapurna Conservation Area Project*. https://ntnc.org.np/project/annapurna-conservation-area-project-acap..
OECD. (2009). *Ressources naturelles et croissance pro-pauvres: enjeux économiques et politiques*. ISBN 978-92-64-04183-7..
Paccagnella, O. (2006). Centering or not centering in multilevel models? The role of group mean and the assessment of group effects. *Evaluation Review, 30*(1), 66–85.
Pfeffermann, D. (1993). The role of sampling weights when modeling survey data. *International Statistical Review, 61*, 317–337.
Pfeffermann, D., Skinner, C., Holmes, D., Goldstein, H., & Rasbash, J. (1998). Weighting for unequal selection probabilities in multilevel models. *Journal of the Royal Statistical Society. Series B, 60*(1), 23–40.
Potthoff, R., Woodbury, M., & Manton, K. (1992). Equivalent sample size and equivalent degree of freedom refinements for inference using survey weights under superpopulation models. *Journal of the American Statistical Association, 87*(418), 383–396.
Rabe-Hesketh, S., & Skrondal, A. (2006). Multilevel modeling of complex survey data. *Journal of the Royal Statistical Society. Series A, 169*(4), 805–827.
Reardon, T., & Vosti, S. A. (1995). Links between rural poverty and the environment in developing countries: Asset categories and investment poverty. *World Development, 23*(9), 1495–1506.
Richardson, R., Fernandez, A., Tschirley, D., & Tembo, G. (2012). Wildlife conservation in Zambia: Impacts on rural household welfare. *World Development, 40*(5), 1068–1081.
Robalino, J. (2007). Land conservation policies and income distribution: Who bears the burden of our environmental efforts? *Environment and Development Economics, 12*, 521–533.
Robalino, J., & Villalobos-Fiatt, L. (2015). Protected areas and economic welfare: An impact evaluation of national parks on local workers' wages in Costa Rica. *Environment and Development Economics, 20*(3), 283–310.
Robinson, E., Albers, H., & Williams, J. (2008). Spatial and temporal aspects of non-timber forest product extraction: The role of community resource management. *Journal of Environmental Economics and Management, 56*, 234–245.
Robinson, E., & Lokina, R. (2011). A spatial-temporal analysis of the impact of access restrictions on forest landscapes and household welfare in Tanzania. *Forest Policy and Economics, 13*, 79–85.
RRN and CECI. (2007). *Development strategies for a new Nepal: A national debate*. http://www.rrn.org.np/wp-content/uploads/2013/07/new_nepal_report.pdf..
Scherr, S. J. (2000). A downward spiral? Research evidence on the relationship between poverty and natural resources degradation. *Food Policy, 25*(4), 479–498.
Sequeira, N., & Nunes, P. (2008). Does tourism influence economic growth? A dynamic panel data approach. *Applied Economics, 40*, 2431–2441.
Shrestha, U., Shrestha, S., Chaudhary, P., & Chaudhary, R. (2010). How representative is the protected areas system of Nepal?. *Moutain Research and Development, 30*(3), 282–294.
Simpson, M. (2007). An integrated approach to assess the impacts of tourism on community development and sustainable livelihoods. *Community Development Journal*, 1–23.
Sims, K. (2010). Conservation and development: Evidence from Thai protected areas. *Journal of Environmental Economics and Management, 60*(2), 94–114.
Snijders, T., & Berkhof, J. (2008). *Handbook of multilevel analysis, chapter: Diagnostic checks for multilevel models* (pp. 141–175). New York: Springer.
Snijders, T., & Bosker, R. (2012). *Multilevel Analysis. An introduction to basic and advanced multilevel modeling*. Sage Publication. second edition.
Spiteri, A., & Nepal, S. (2008a). Distributing conservation incentives in the buffer zone of Chitwan National Park, Nepal. *Environmental Conservation, 35*(1), 76–86.
Spiteri, A., & Nepal, S. (2008b). Evaluating local benefits from conservation in Nepal's Annapurna Conservation Area. *Environmental Management, 42*(3), 391–401.
Steenbergen, M., & Jones, B. (2002). Modeling multilevel data structures. *American Journal of Political Science*, 218–237.
Theng, S., Qiong, X., & Tatar, C. (2015). Mass tourism vs alternative tourism?. *Challenges and new positionings. Etudes caribéennes*, 31–32.
TURGAN. (2010). *Tourist guide association of Nepal.* http://tourguidenepal.org.np/about-us..
UNDP. (2015). *Enhancing access to financial services.* http://www.np.undp.org/content/nepal/en/home/operations/projects/closed-projects/poverty-reduction/eafs.html..
UNDP. (2016). *Rapport sur le développementn humain 2016.* http://hdr.undp.org/sites/default/files/HDR2016_FR_Overview_Web.pdf..
UNEP (2014). Mapping the world's special places. http://www.unep-wcmc.org/featured-projects/mapping-the-worlds-special-places..
Weinberg, A., Bellows, S., & Ekster, D. (2002). Sustaining ecotourism: Insights and implications from two successful case studies. *Society and Natural Resources, 15*(4), 371–380.
Wooldridge, J. (2003). Cluster-sample methods in applied econometrics. *The American Economic Review, 93*(2), 133–138.
World Bank. (2016). *The Nepal earthquakes of 2015: One year on*. http://blogs.worldbank.org/endpovertyinsouthasia/nepal-earthquakes-2015-one-year..
WTO. (2013). *UN General Assembly: Ecotourism key to eradicating poverty and protecting environment*. http://media.unwto.org/press-release/2013-01-03/un-general-assembly-ecotourism-key-eradicating-poverty-and-protecting-envir..
WTTC. (2015). *Travel and tourism. Economic impact 2015.* Nepal..
WWF. (2019). Langtang National Park and Buffer Zone Support Project. http://www.wwfnepal.org/about_wwf/where_we_work/shl/langtang/..
Yergeau, M. (2015). Conservation, écotourisme et bien-être: leçons népalaises. *Revue d'économie du développement, 23*(1), 129–165.
Yergeau, M. (2017). *Enquête sur les ménages, l'environnement et le tourisme dans les zones protégées - Népal, 2013*. Rapport méthodologique et statistique. Working Paper. Grédi. 17–04..
Yergeau, M., Boccanfuso, D., & Goyette, J. (2017). Linking conservation and welfare: A theoretical model with application to Nepal. *Journal of Environmental Economics and Management, 85*, 95–109.
Yunis, E. (2004). Chief sustainable development of tourism, World Tourism Organization. http://www.regione.toscana.it/regione/multimedia/RT/documents/1219927391372_eng_yunis.pdf..